

Review

Digital Disruption in Accounting and Financial Reporting: AI-Supported Decision Support and Human Judgement in the Hospitality Industry

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Abstract

Artificial intelligence (AI), business intelligence (BI) and analytics are increasingly used in hotel accounting, financial reporting and performance management. Existing research, however, has concentrated mainly on prediction, automation and operational optimisation. Their integration with the critical interpretation of accounting information and human judgement remains less clearly developed. This study provides a structured review and bibliometric mapping of research on AI-supported accounting and financial reporting in the hospitality industry. It adopts a structured bibliometric review combining science mapping with qualitative content-oriented interpretation. The review comprises three complementary search streams addressing: (i) AI, BI and analytics in hotel accounting; (ii) AI-supported reporting, dashboards and decision-support systems; and (iii) the broader contextual literature on human judgement and the interpretation of accounting information. The results identify machine learning, revenue management, forecasting and dynamic pricing as the most prominent and structurally influential areas within the retrieved literature. Research on reporting interpretation, dashboard-based judgement, anomaly detection and human validation is more fragmented and remains weakly integrated across the mapped literature. The principal research gap therefore concerns the limited connection between AI-supported technologies, reporting outputs and human interpretive judgement, rather than the absence of relevant research in these areas. The study proposes a human-centred perspective on AI in hotel accounting and identifies future research directions in which AI supports critical interpretation, professional judgement and responsible managerial decision-making.

Keywords: artificial intelligence; business intelligence; hotel accounting; decision support; human judgement



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1. Introduction

Hotel accounting increasingly depends on complex flows of financial, operational and performance information (Mariani et al., 2018). Accountants, managers and other decision-makers must interpret reports, dashboards, key performance indicators and revenue management data under time pressure, operational uncertainty and growing technological mediation (Carneiro et al., 2023; Gultom et al., 2026). Accounting information must therefore be recorded and reported but also read and translated into managerial judgement (Heo & Schegg, 2026).

Artificial intelligence (AI), business intelligence (BI) and analytics are increasingly used in hospitality management accounting, financial reporting, performance evaluation, dashboards and decision-support systems (Mariani et al., 2018; Carneiro et al., 2023). These technologies can identify patterns, anomalies, inconsistencies, missing indicators and weak interpretations (Gultom et al., 2026; Heo & Schegg, 2026). They may also reduce the risks of superficial report and dashboard reading, particularly when professionals rely on visible indicators such as occupancy, revenue per available room (RevPAR) or revenue growth without considering cost structures, profitability, operational context or strategic trade-offs (Heo & Schegg, 2026; Fatima & Elbanna, 2020).

However, the growing use of AI and analytics in accounting and performance management does not remove the need for human judgement. In hospitality accounting, interpretation depends on contextual knowledge, professional experience, strategic reasoning and ethical responsibility (Heo & Schegg, 2026; Gultom et al., 2026). A dashboard may indicate a positive trend, but human judgement is still required to determine whether it represents sustainable performance, short-term compensation, operational risk or a fragile managerial narrative (Mariani et al., 2018; Tajeddini et al., 2026). AI should therefore be understood not only as a tool for automation, but also as possible support for critical reading and interpretive decision-making (Heo & Schegg, 2026).

The research gap addressed in this study lies in this relationship. Although AI, BI and analytics are increasingly used in hospitality accounting, financial reporting, dashboards and decision-support systems, the literature remains largely organised around automation, performance monitoring and managerial decision support (Mariani et al., 2018; Carneiro et al., 2023; Gultom et al., 2026). Less attention has been given to AI as a support tool for the critical reading and interpretation of hospitality accounting reports, particularly for identifying inconsistencies, omissions, anomalies and weak interpretations while preserving human judgement in decision-making (Heo & Schegg, 2026). The gap addressed here should therefore not be understood as an absence of research on AI, reporting or human judgement individually, but as their limited thematic and conceptual integration within the mapped literature. This gap corresponds to the paper's initial conceptual framing, which treats AI, reporting and dashboards, and human judgement as related but insufficiently integrated dimensions of hotel accounting research.

Based on this gap, the study addresses the following research question: How does the literature on AI, BI and analytics in hospitality accounting address report interpretation, decision support and human judgement, and what future research lines emerge from bibliometric science mapping of this field?

To answer this question, the study employs a structured bibliometric review combining science mapping with qualitative content-oriented interpretation. The review is organised into three search streams. The first maps the broader literature on AI, BI and analytics in hospitality accounting and performance management. The second focuses on AI-supported reporting, dashboards, key performance indicators (KPIs) and decision-support systems. The third captures the broader literature on how accounting and performance information is interpreted and judged by human decision-makers. Because this stream does not require AI-related terminology, it is used as a contextual reference for the human judgement dimension, rather than as direct evidence of AI-supported human judgement. This structure enables comparison of the field's technological, informational and human dimensions and assesses whether they are developing together or remain fragmented across separate bodies of literature.

2. Conceptual Background on AI, Reporting and Human Judgement in Hospitality Accounting

2.1. AI, BI and Analytics in Hospitality Accounting and Performance Management

Hotel accounting must account for volatile revenues and indirect operating costs. [Bhuiyan et al. \(2023\)](#) identify several tools for managing these pressures, including machine learning algorithms that analyse data in real time and adjust room rates dynamically to avoid selling below marginal cost or losing margin during periods of peak demand. Predictive analytics (PA) transforms raw booking data into financial projections, including forecasts of future revenue. It can also improve the consistency of financial reports and projections for auditing and help prevent artificially inflated budgets ([Kaviya & Meera, 2026](#)). By combining weather forecasts, local events and occupancy data, AI can predict demand and support reductions in personnel costs ([Bhuiyan et al., 2023](#)).

Within hotel revenue management (RM), Big Data Analytics (BDA) is used for price optimisation, forecasting and demand management. The combined use of BDA and PA has been associated with improved financial performance and managerial decision-making ([Carneiro et al., 2023](#); [Kaviya & Meera, 2026](#)). Analytics tools also monitor key performance indicators (KPIs) in real time, supporting profit improvement and the optimisation of RevPAR ([Bhuiyan et al., 2023](#)).

When supported by machine learning, PA can outperform traditional models in hotel performance evaluation. It combines performance and behavioural variables, including Average Daily Rate (ADR), lead time, length of stay and cancellation rates. These projections inform dynamic pricing, room inventory management and staffing plans based on expected demand ([Kaviya & Meera, 2026](#)).

Business intelligence (BI) extends this analytical capacity by combining external market data with internal company data. It addresses three related questions: “What happened?” in accounting terms; “What could happen?” as a basis for financial and budgetary planning; and “What should we do?” to guide real-time action ([Mariani et al., 2018](#)). Despite these applications, AI tools directly connected to hotel performance indicators and accounting remain scarce. [Nikić and Laškarin Ažić \(2025\)](#) nevertheless identify AI as a central driver of change in hotel revenue management.

The effectiveness of these tools does not depend solely on their mathematical capacity for automation and performance optimisation. [Nikić and Laškarin Ažić \(2025\)](#) argue against fully automated approaches and link the success of revenue management to transparency and co-intelligence between algorithms and human analysts. This requires interpretable predictive models that allow critical judgement and human interpretation. Such mediation is also necessary to address the ethical and psychological dimensions of the market, including perceptions of price fairness and consumer psychology, which isolated automated systems cannot yet fully encode.

2.2. AI-Supported Reporting, Dashboards, KPIs and Decision-Support Systems

Accounting reports and operational dashboards in the hotel industry are not neutral repositories of information. They determine what becomes visible by prioritising lagging financial metrics over intangible and operational indicators ([Fatima & Elbanna, 2020](#); [Nunes & Machado, 2012](#)). In traditional management systems, an excessive focus on budgets and costs can restrict managers’ analytical capacity ([Nunes & Machado, 2012](#)). The Balanced Scorecard (BSC) broadens this perspective by incorporating additional dimensions and developing from a monitoring tool into a strategic management system. BI and analytics can support more complex interpretation and reduce superficial readings of performance information ([Fatima & Elbanna, 2020](#)). However, visually dense dashboards may encourage fragmented interpretations based on colour signals, simplified alerts or isolated KPIs. The

resulting cognitive load and false sense of control can limit critical analysis of the hotel's actual performance (Yandamuri, 2024).

The convergence of BI, analytics and AI offers an alternative to static reporting by changing how accounting data are organised and presented (Gultom et al., 2026; Tajeddini et al., 2026). BI integrates large and diverse flows of raw data from multiple systems and converts them into structured information. Its function therefore extends beyond visualisation to the analysis of performance across areas such as demand and occupancy forecasting, dynamic pricing, staff scheduling and service quality management based on digital reviews (Tajeddini et al., 2026). Machine learning and PA can identify patterns in complex historical data, generate predictive recommendations and reduce market uncertainty. Their use nevertheless remains concentrated on short-term efficiency, with less attention to long-term strategic planning. These systems should support managers' interpretive capacity and critical judgement without replacing final decision-making (Gultom et al., 2026).

Transforming hotel dashboards into tools for critical interpretation requires the integration of BI with advanced analytical models. Ryoo et al. (2026) show that Autoregressive Integrated Moving Average (ARIMA) predictive models and interactive drill-down functions can change the user's role. Instead of encouraging superficial readings based on basic visual cues, the system supports proactive interpretation by setting alert thresholds according to statistical forecasting errors. The dashboard thus develops from a monitoring mechanism into a decision-support system (DSS) that reduces the biases associated with viewing KPIs in isolation (Ryoo et al., 2026).

2.3. Human Judgement, Critical Reading and Interpretation of Hotel Accounting Information

In this study, human judgement refers to the evaluative process through which managers and accounting professionals interpret, contextualise and assess accounting and performance information before reaching a decision, consistent with research emphasising contextual interpretation and the evaluative role of human decision-makers in hotel accounting and revenue-management settings (Heo & Schegg, 2026; Bendoly, 2013; Mohammed & Denizci Guillet, 2025). It is therefore treated as distinct from decision-making, which refers here to the subsequent choice or action.

Digital dashboards provide real-time data through highly visual interfaces, but access to data does not by itself ensure sound decision-making. One of the main challenges for small and medium-sized enterprises (SMEs) in the hotel sector is the limited validation of cause-and-effect relationships between operational and financial indicators. This methodological weakness increases the risk of superficial assessments based mainly on how information is displayed (Quesado & Miranda, 2026).

Performance reports and KPIs, including RevPAR, ADR and Gross Operating Profit per Available Room (GOPPAR), do not produce meaning independently. Decision-makers must interpret them in relation to the relevant macroeconomic and microeconomic conditions (Heo & Schegg, 2026). Reading isolated indicators passively can therefore be misleading. During disruption or high uncertainty, conventional monitoring routines may be insufficient, and deeper sensemaking is required to avoid biased interpretations or excessive reliance on familiar contexts and established assumptions (Visentin et al., 2021).

The visual advantages of advanced analytical tools may also be weakened by limited data absorption capacity, poorly established organisational routines, cognitive bias and inertia among senior managers (Tajeddini et al., 2026). Easy access to data and the proliferation of visual interfaces can encourage cognitive shortcuts. Rapid reading and superficial analysis may cause users to overlook relationships between indicators, reducing the quality of the final diagnosis (M. An et al., 2026). Advanced AI modules can help turn dashboards into tools for critical and contextualised analysis (Yandamuri, 2024). By reducing the time

required to process raw data and dense reports, AI can shift managerial attention from information collection towards higher-level interpretation (R. An et al., 2026).

Automation does not remove the role of human decision-makers in hospitality. Predictive technologies and language models instead require a hybrid human–AI framework in which professional judgement and scepticism protect against superficial interpretation, hidden algorithmic bias and passive acceptance of automated metrics (Abbas, 2026). This transition requires strategic preparation. Hotels need to develop managers' cognitive flexibility through scenario analysis, AI literacy training and a broader range of monitored metrics (Heo & Schegg, 2026).

A human-in-the-loop methodology and a clear governance framework are also required when managers override system recommendations. Such arrangements allow technology to extend cognitive capacity and support proactive analysis without replacing experiential knowledge (Yandamuri, 2024). Even when dashboards are highly structured, human verification and traceability remain necessary to limit automation bias (R. An et al., 2026). AI should therefore support critical scrutiny rather than become a shortcut to decision-making (M. An et al., 2026).

3. Methodology

3.1. Research Design and Methodological Rationale

This study adopts a structured literature review design combining bibliometric science mapping with qualitative interpretive analysis. This design was selected because the study aims to map the thematic structure of literature and, at the same time, interpret how different research themes are connected, fragmented or insufficiently integrated (Cardoso et al., 2024).

Bibliometric science mapping allows researchers to examine the conceptual and intellectual organisation of a research field through visual and quantitative techniques (Chen, 2017; Cobo et al., 2011). Previous bibliometric studies have also shown the relevance of this approach for analysing research performance, scientific positioning and thematic development in interdisciplinary fields (Cardoso et al., 2020, 2021). However, bibliometric outputs require interpretation, since clusters, networks and thematic maps identify patterns of association but do not explain their conceptual meaning by themselves (Cardoso et al., 2024; Degn et al., 2019; Klarin, 2024). For this reason, recent methodological contributions have recommended combining bibliometric analysis with qualitative or integrative forms of interpretation, particularly when the aim is to move from mapping to research agenda development (Kahlke et al., 2026; Szrajber & Alon, 2026).

The main objective of the study is as follows: To review and bibliometrically map the literature on artificial intelligence, business intelligence and analytics in hotel accounting, with particular attention to financial and management reports, dashboards, performance indicators, decision support and human judgement.

To achieve this objective, the study pursued the following specific objectives:

1. To identify the main thematic clusters emerging from each of the three search streams through keyword co-occurrence analysis based on author keywords.
2. To analyse the thematic positioning of each subcorpus, distinguishing motor themes, basic themes, niche themes, and emerging or declining themes.
3. To compare the bibliometric outputs obtained from the three subcorpora in order to identify thematic convergences, divergences, and underexplored areas in the literature.
4. To examine how mapped literature integrates artificial intelligence, report and dashboard interpretation, decision support, and human judgement in the context of hotel accounting.

5. To propose future research lines on AI-supported critical reading, report interpretation, anomaly detection, and human judgement in hotel accounting, based on the comparative analysis of the three subcorpora.

This methodological structure allowed the study to combine a systematic search process, bibliometric mapping and interpretive comparison across the three streams. The overall design was therefore aligned with the purpose of mapping the field, comparing its main thematic directions and identifying future research opportunities.

3.2. Data Source and Search Strategy

The bibliographic search was conducted in Scopus on 24 May 2026, using the TITLE-ABS-KEY field, which retrieves terms from titles, abstracts and author keywords. Scopus was selected because it provides broad coverage of peer-reviewed literature across management, accounting, computer science, decision sciences, finance and interdisciplinary research areas. Its use is also consistent with previous bibliometric studies that have relied on this database to map scientific production, research positioning and thematic development (Cardoso et al., 2025). A single bibliographic database was retained to ensure a consistent metadata structure and the same indexing basis across the three subcorpora, thereby supporting comparability in the subsequent bibliometric analyses. This choice prioritised methodological consistency rather than exhaustive coverage of all potentially relevant publications.

To reflect the multidimensional nature of the topic, the search strategy was organised into three complementary streams rather than treated as a single undifferentiated body of literature. This structure made it possible to separate three analytical perspectives that are closely related but conceptually distinct: the technological dimension, the reporting and dashboard dimension, and the human interpretive dimension.

The first stream captured the broader literature on artificial intelligence, business intelligence and analytics in hotel accounting and performance management. It was designed to identify studies that connect analytical technologies with accounting-related practices, financial performance, budgeting, cost control, revenue management and key performance indicators. The second stream adopted a narrower focus by identifying studies in which AI, business intelligence, analytics or decision-support systems were explicitly associated with reports, dashboards, KPIs and performance information. This stream was therefore intended to isolate the literature concerned with the transformation of accounting and performance data into reporting, visualisation and decision-support outputs. Because revenue management was included as a predefined accounting- and performance-related term in all three streams, its subsequent prominence is interpreted as a characteristic of the retrieved subcorpora rather than as an unbiased estimate of its prevalence in the wider field.

The third stream addressed the human side of the research problem. It focused on interpretation, comprehension, sensemaking, critical reading, decision-making and professional judgement in relation to accounting reports, dashboards, KPIs, revenue management and financial performance. Unlike Streams 1 and 2, it did not require AI-related terminology and was therefore used as a contextual reference for the human-judgement dimension, rather than as direct evidence of AI-supported human judgement. Its inclusion was essential because the study does not treat accounting and performance information only as data to be processed, but also as information that must be interpreted, evaluated and used by human decision-makers.

As summarised in Figure 1, the three streams produced different corpus sizes, reflecting their distinct conceptual scope and level of specificity. Stream 1 and Stream 3 generated broader corpora suitable for bibliometric science mapping, whereas Stream 2 resulted in a smaller but more focused corpus. The smaller Stream 2 corpus was retained because it

captured the explicitly defined intersection between AI-supported technologies, reporting, dashboards, KPIs and decision-support systems. Its size was not treated as evidence of the maturity or emergence of the broader research field. For this reason, Stream 2 was analysed through exploratory bibliometric mapping complemented by qualitative interpretation.

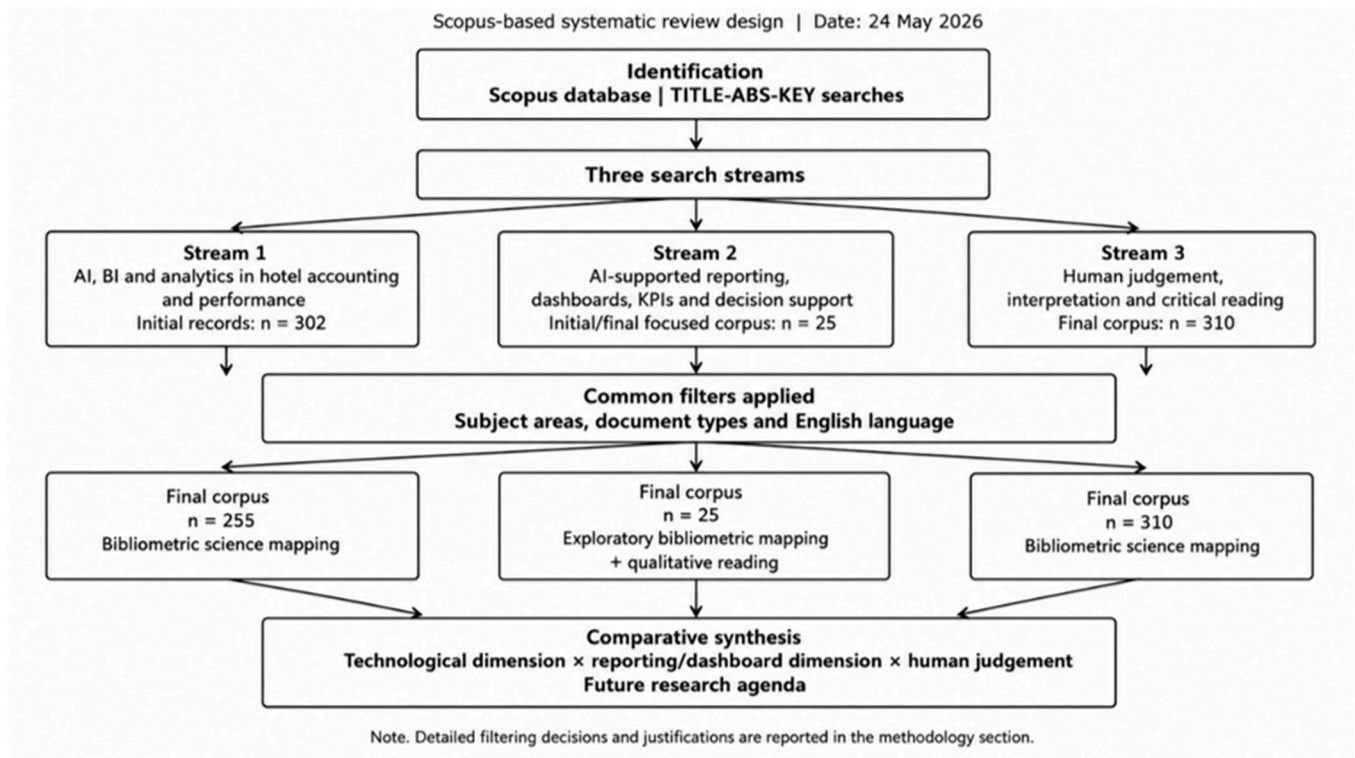


Figure 1. Three-stream search strategy and document screening process. **Note.** AI—artificial intelligence; BI—business intelligence; KPI—key performance indicator; n—number of documents. The searches were conducted in Scopus using the TITLE-ABS-KEY field. Full details of the filters, inclusion criteria and screening decisions are provided in the Section 3.

The same filtering logic was applied across the three streams to ensure methodological consistency. Full details on the search strings, retained subject areas, document types, language criteria, inclusion and exclusion decisions, and final corpus size of each stream are presented in Appendix A.

3.3. Data Analysis Procedure

The data analysis followed a bibliometric science-mapping approach applied consistently to the three search streams. After exporting the records from Scopus, each subcorpus was analysed with Bibliometrix/Biblioshiny to generate keyword co-occurrence networks and thematic maps. These outputs were then interpreted qualitatively and compared across streams, with the aim of identifying thematic convergences, divergences and areas that remain weakly connected across the mapped literature.

To support this interpretive stage, a qualitative content-oriented reading was conducted after the bibliometric outputs had been generated. For each network, thematic map and interpretive pattern, the documents most directly associated with the identified terms or themes were examined through their titles, abstracts and author keywords. This step made it possible to identify the key papers that corroborated each result, distinguish central from complementary evidence, and avoid attributing meanings to the maps that were not supported by the content of the retrieved literature.

Author keywords were used as the analytical field in both procedures, as they represent the concepts that authors explicitly select to describe the focus of their studies. This

choice made it possible to examine the conceptual structure of each subcorpus through the vocabulary used by the literature itself. For the keyword co-occurrence networks, a maximum of 50 nodes was retained, isolated nodes were removed, and a minimum threshold of two edges was applied. This reduced noise and ensured that the maps focused on connected and analytically meaningful keyword relationships. The networks were normalised using the association strength method, which is appropriate for identifying substantive associations between terms rather than simply reflecting their absolute frequency.

The network visualisations were produced using the automatic layout option, with a repulsion force of 0.1. Label overlap was avoided to improve readability, and only minor visual adjustments were made to enhance clarity, without changing the analytical content of the maps. Node colour by year was not applied, since the purpose of the analysis was to examine the thematic structure of each stream rather than its temporal evolution. Clusters were identified using the Walktrap algorithm, which detects groups of keywords according to the strength of their connections. The interpretation of each network combined visual inspection with centrality indicators, namely betweenness, closeness and PageRank. These measures helped identify the most influential concepts, the main bridging terms and the relative position of each keyword within the network.

The thematic maps were also generated from author keywords and used to assess the strategic positioning of the themes in each subcorpus. The same parameters were maintained across the three streams to ensure comparability: 50 words, a minimum cluster frequency of 1, two labels per cluster, a label size of 0.3, community repulsion set to 0, and the Walktrap clustering algorithm. The maps position themes according to centrality and density. Centrality indicates the relevance of a theme within the overall structure of the subcorpus, while density reflects its internal development and cohesion. Based on these two dimensions, the themes were interpreted as motor themes, basic themes, niche themes, or emerging or declining themes.

For Streams 2 and 3, the thematic maps were generated directly in Biblioshiny. For Stream 1, the same parameters were applied using the Bibliometrix package in R version 4.5.1. This subcorpus had a denser keyword structure, and the Biblioshiny graphical interface did not render the map reliably with the predefined settings. The adjustment affected only the software environment and did not change the analytical criteria or the comparability of the results. It allowed the same procedure to be applied consistently across the three subcorpora, which were then compared in terms of conceptual structure, thematic maturity and the integration of artificial intelligence, reporting, decision support and human judgement in hotel accounting.

4. Results and Discussion

4.1. Thematic Structure of AI, BI and Analytics in Hotel Accounting and Performance Management

This section examines Stream 1, which corresponds to the broader subcorpus on artificial intelligence (AI), business intelligence (BI) and analytics in hotel accounting and performance management. It is organised into complementary analytical steps. First, the author keyword co-occurrence network identifies the dominant thematic clusters. Second, the thematic map positions these themes according to centrality and density. Together, these analyses show whether this broader literature is mainly structured around predictive, operational and performance-oriented applications, or whether it also integrates reporting interpretation, dashboard-based judgement and human decision-making.

4.1.1. Keyword Co-Occurrence Network: Dominant Thematic Clusters

This subsection examines the author keyword co-occurrence network for Stream 1 in order to identify the dominant thematic clusters in the broader literature on AI, BI and analytics in hotel accounting and performance management.

The keyword co-occurrence network for Stream 1 (Figure 2) indicates that the literature is strongly structured around two central technological concepts: machine learning and artificial intelligence. Among these, machine learning emerges as the most influential node in the network, presenting the highest betweenness centrality and PageRank values (betweenness = 398.081; PageRank = 0.203). This confirms its role as the main organising concept of the corpus and as the principal bridge between methodological approaches and hotel-related applications. Its close association with revenue management (betweenness = 175.898; PageRank = 0.119), dynamic pricing (betweenness = 0.623; PageRank = 0.034), demand forecasting (betweenness = 0.080; PageRank = 0.024), hospitality (betweenness = 1.641; PageRank = 0.035), forecasting, optimisation, random forest, neural networks and predictive analytics shows that the strongest thematic structure within this subcorpus is oriented towards predictive modelling and operational decision support in hotel revenue management.

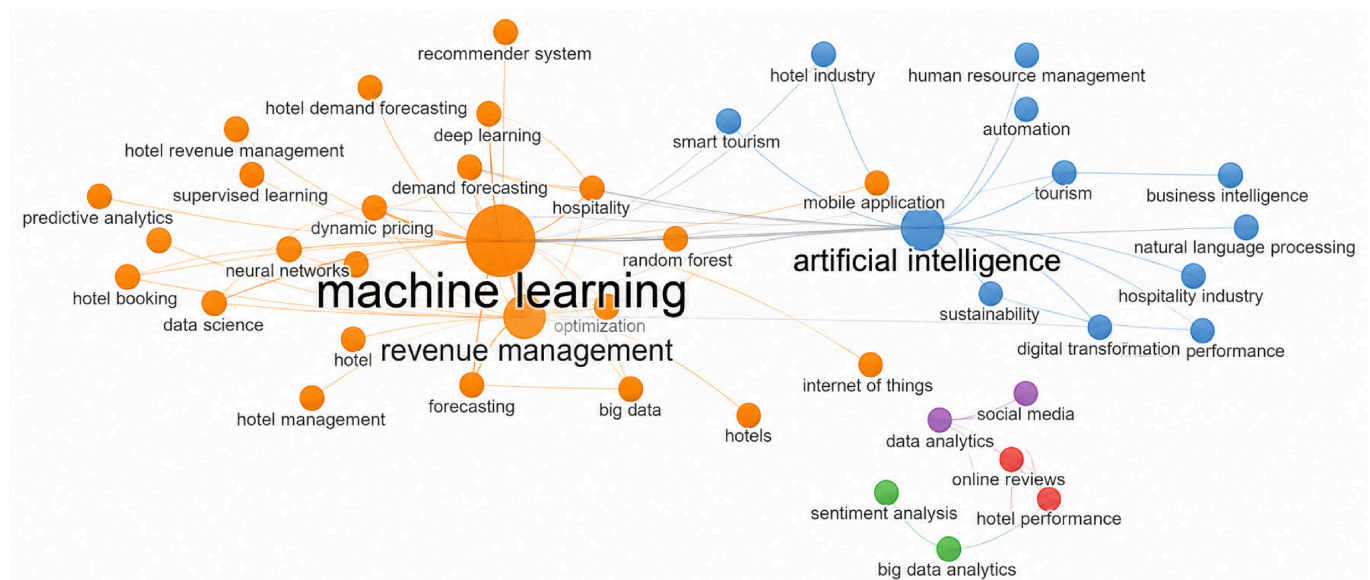


Figure 2. Keyword co-occurrence network of AI and machine learning in the hospitality industry.

The prominence of revenue management reinforces this interpretation. As the second most influential node in the machine learning cluster, it functions as the main application domain through which algorithmic and predictive techniques have been integrated into hospitality research. The structure of this cluster suggests that AI-related research in this stream has developed primarily around forecasting demand, optimising prices, predicting bookings and improving operational performance. This pattern is directly supported by [Pereira and Cerqueira \(2022\)](#), who examined hotel demand forecasting for revenue management using machine learning regression methods, and by [António et al. \(2019\)](#), who connected big data, automated machine learning and decision-support systems with the prediction of hotel booking cancellations. [Das et al. \(2021\)](#) further corroborated this orientation by focusing on market forecasting for hotel revenue management, while [Brunato and Battiti \(2020\)](#) supported the optimisation dimension through intelligent heuristics and simulators in hotel revenue management. Within this subcorpus there is a well-developed and structurally central research line focused on prediction and optimisation.

The artificial intelligence cluster presents a broader but more dispersed thematic configuration. Artificial intelligence is the most central node in this cluster (betweenness = 190.677; PageRank = 0.099), connecting terms such as tourism (betweenness = 35.000; PageRank = 0.022), business intelligence, digital transformation, automation, natural language processing, sustainability, hospitality industry, hotel industry and human resource management. This broader configuration is consistent with [Buhalis and Leung \(2018\)](#), who frame smart hospitality around interconnectivity, interoperability and data-driven ecosystems, and with [Dogru et al. \(2025\)](#), who position generative AI across multiple hospitality and tourism functions. In the network, however, these applications appear more dispersed than the machine learning and revenue management cluster, and the betweenness values of many nodes are zero, indicating that these topics are more peripheral and less involved in connecting different parts of the network. Therefore, although AI appears as a central term, its applications remain fragmented across different managerial and technological domains.

Overall, the keyword co-occurrence network shows that Stream 1 is dominated by predictive and operational applications of AI and machine learning, particularly in hotel revenue management. The strongest author-supported evidence points to forecasting, booking-cancellation prediction, dynamic pricing and optimisation. By contrast, the network offers weaker evidence of an integrated literature on accounting report interpretation, dashboard-based judgement or human decision-making. This finding is important for the paper because it shows that the retrieved technological literature is strongly concentrated around prediction and performance optimisation rather than around AI-supported critical interpretation of accounting information.

4.1.2. Thematic Map: Motor, Basic, Niche and Emerging Themes

This subsection analyses the thematic map of Stream 1 in order to assess the strategic positioning of its main themes according to centrality and density.

As shown in Figure 3, the thematic map was used to examine the strategic positioning of the main themes in Stream 1, distinguishing between motor themes, basic themes, niche themes and emerging or declining themes. Overall, the map shows that this subcorpus is mainly organised around a predictive and operational logic, with machine learning/revenue management positioned as the main motor theme. This means that the theme is both central to the corpus and internally well developed. It represents the most central and internally developed research line in this stream, confirming the strong presence of studies focused on forecasting, pricing, optimisation and revenue-related decision support in hotel contexts. This position is directly corroborated by [Pereira and Cerqueira \(2022\)](#), [António et al. \(2019\)](#), [Das et al. \(2021\)](#), and [Brunato and Battiti \(2020\)](#), whose abstracts consistently support forecasting, booking cancellation prediction, dynamic pricing and optimisation in hotel revenue management.

The theme deep learning/hotel industry also appears in the upper part of the map, close to the boundary between niche and motor themes. This suggests a relatively developed topic, although less central than machine learning/revenue management. This specialised position is consistent with studies that apply advanced analytical techniques to hotel-industry problems, such as [Binesh et al. \(2024\)](#), who used artificial neural networks for room price forecasting.

In the basic themes quadrant, the map includes financial performance/hospitality industry, artificial intelligence/tourism and data analytics/social media. These themes are relevant to the overall structure of the corpus, but they are less internally developed than the motor theme. This indicates that AI, tourism, hospitality performance and social media analytics are important transversal topics, but their conceptual and methodological integration remains less consolidated. In particular, artificial intelligence/tourism appears

as a broad organising theme, while financial performance/hospitality industry shows the presence of performance-related concerns without yet forming a highly developed research core. The financial performance dimension is supported by [Carneiro et al. \(2023\)](#), who connected big data analytics with company performance in the hotel sector. The broader artificial intelligence/tourism theme is corroborated by [Buhalis and Leung \(2018\)](#) and [Dogru et al. \(2025\)](#), who framed artificial intelligence across wider hospitality and tourism ecosystems. The data analytics/social media theme is supported by [Bagherzadeh et al. \(2021\)](#) and [Gour et al. \(2021\)](#), whose abstracts focused on online reviews, sentiment-related analysis and digital data as sources of managerial insight.

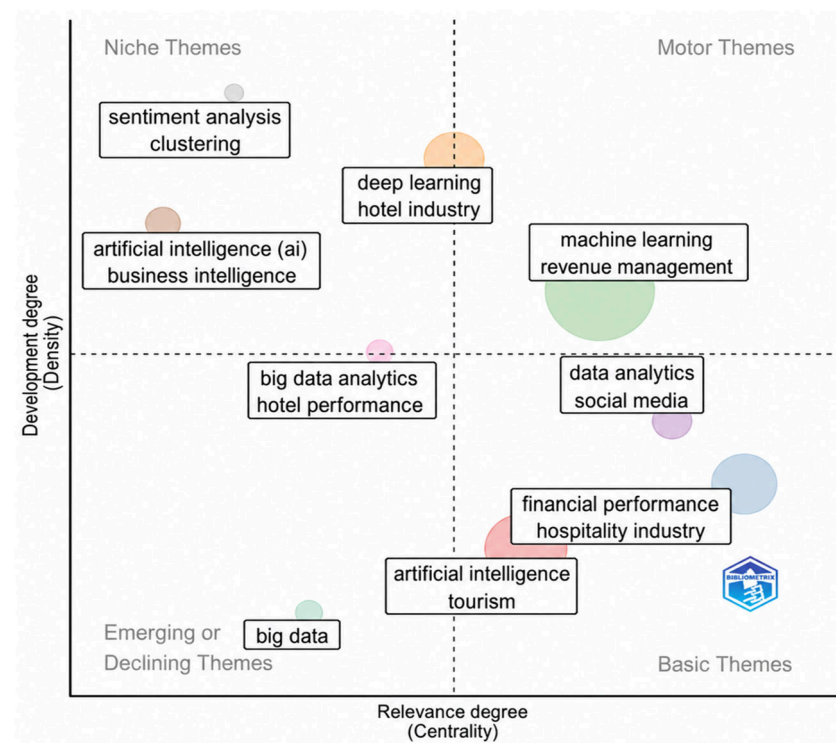


Figure 3. Thematic map of artificial intelligence, business intelligence and analytics themes in hotel accounting and performance management.

The niche themes include sentiment analysis/clustering and artificial intelligence (AI)/business intelligence. Their position indicates that they are relatively developed but less central to the corpus. These themes represent specialised areas, probably associated with text mining, review analysis, customer opinion classification and business intelligence applications, but they remain somewhat detached from the dominant machine learning and revenue management structure. This reading is supported by [Bagherzadeh et al. \(2021\)](#), who reinforced the sentiment analysis dimension, and by [Ibrahim and Handayani \(2022\)](#), whose review directly addressed business intelligence frameworks and functionalities in tourism organisations.

The emerging or declining themes quadrant includes big data, while big data analytics/hotel performance appears near the central boundary of the map. This suggests that broad references to big data are not currently central or strongly developed in this subcorpus. The field seems to have moved from general big data terminology towards more specific analytical approaches, such as machine learning, deep learning, data analytics and business intelligence. [Carneiro et al. \(2023\)](#) support this shift by showing how big data analytics is being translated into performance-oriented applications in the hotel sector, rather than remaining only at the level of broad conceptual discussion.

The thematic map shows that Stream 1 is dominated by machine learning-driven revenue management as the most central and developed theme. Other relevant themes, such as artificial intelligence in tourism, financial performance, social media analytics, sentiment analysis and business intelligence, are present but occupy less consolidated positions. The map therefore refines the previous network analysis by showing that Stream 1 is not limited to a single predictive cluster but includes a broader thematic structure with different levels of internal development and centrality. Even so, the mapped literature shows stronger thematic development in predictive and operational applications than in human judgement, dashboard interpretation or artificial intelligence-supported accounting decision-making.

4.1.3. Interpretation of Stream 1: Technological and Analytical Orientation of the Field

This subsection synthesises the keyword co-occurrence network and the thematic map to clarify the dominant orientation of the broader literature on artificial intelligence, business intelligence and analytics in hotel accounting and performance management.

The evidence from the network and the thematic map points to a literature mainly oriented towards predictive analytics, operational optimisation and revenue management decision support. The strongest signal is concentrated around machine learning applications for demand forecasting, booking cancellation prediction, pricing and performance-related decision-making, as supported by [Pereira and Cerqueira \(2022\)](#), [António et al. \(2019\)](#), [Das et al. \(2021\)](#), and [Brunato and Battiti \(2020\)](#).

The broader artificial intelligence cluster adds another layer to this picture. Artificial intelligence is discussed across wider hospitality and tourism ecosystems, including smart hospitality, digital interconnectivity and multiple organisational functions, as suggested by [Buhalis and Leung \(2018\)](#) and [Dogru et al. \(2025\)](#). However, this broader presence does not form a coherent research line on accounting report interpretation, dashboard-based judgement or human decision-making.

The secondary themes point in the same direction. Big data analytics and hotel performance, online reviews and sentiment-related analysis, and business intelligence show how digital data can support managerial insight, as illustrated by [Carneiro et al. \(2023\)](#), [Bagherzadeh et al. \(2021\)](#), [Gour et al. \(2021\)](#), and [Ibrahim and Handayani \(2022\)](#). Yet these themes remain adjacent to, rather than integrated with, the critical interpretation of accounting reports, dashboards and key performance indicators.

Stream 1 therefore provides strong evidence that the retrieved literature is structurally concentrated around forecasting, revenue management, optimisation, analytics and performance support. It provides much weaker evidence of integrated literature on artificial intelligence-supported accounting interpretation, dashboard-based judgement, anomaly reading or human validation of decision-support outputs. The contrast within this subcorpus therefore lies less in the presence or absence of these topics than in their different levels of thematic integration.

4.2. AI-Supported Reporting, KPIs and Decision-Support Outputs in Hotel Accounting

This section examines Stream 2, which corresponds to the subcorpus focused on artificial intelligence-supported reporting, key performance indicators (KPIs) and decision-support outputs in hotel accounting. It is organised into three complementary analytical steps. First, Section 4.2.1 addresses Objective 1 by examining the author keyword co-occurrence network. Second, Section 4.2.2 addresses Objective 2 by analysing the thematic map according to centrality and density. Third, Section 4.2.3 addresses Objective 4 by qualitatively reading the 25 documents to assess how reports, dashboards, KPIs and decision-support outputs are framed in the corpus.

4.2.1. Keyword Co-Occurrence Network: Focused Signals of Data-Driven Decision Support

This subsection examines the author keyword co-occurrence network to determine whether these subcorpus forms diversified thematic clusters or, instead, concentrates around a narrower set of connected terms. As shown in Figure 4, the keyword co-occurrence network for Stream 2 is highly compact, containing only one cluster composed of five inter-connected terms: data science, decision support system, dynamic pricing, hotel revenue management system and machine learning. All nodes belong to Cluster 1 and present identical centrality values (betweenness = 0.000; closeness = 0.250; PageRank = 0.200), indicating that no term performs a bridging role between different thematic areas.

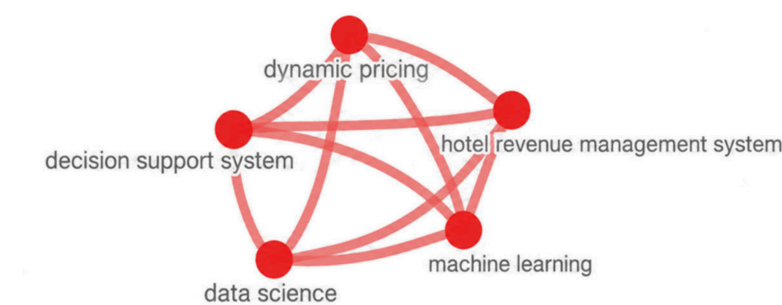


Figure 4. Keyword co-occurrence network of data-driven decision-support terms in hotel accounting.

This result suggests that the subcorpus has a narrow and homogeneous thematic structure. Rather than showing multiple clusters or differentiated conceptual communities, it is concentrated around the relationship between data-driven methods and revenue-related decision support in hotels. This pattern is directly corroborated by [Saitta et al. \(2024, 2026\)](#), whose abstracts focus on dynamic price prediction in hotel revenue management systems and describe machine learning as a way to support revenue managers in monitoring key performance indicators, future days of stay, market conditions and external factors when adjusting room prices. These two studies therefore provide the closest textual support for the five terms that appear together in the network.

The presence of decision support system, together with machine learning, data science and dynamic pricing, indicates that this subcorpus is more focused on operational decision support than on broader debates around accounting interpretation, dashboard reading or human judgement. This operational interpretation is also compatible with [Ibrahim and Handayani \(2022\)](#), who discuss business intelligence (BI) frameworks and functionalities as support for decision-making in tourism organisations. However, this study should be read as complementary evidence of data-supported decision-making, not as direct evidence of the dynamic-pricing and hotel revenue management cluster itself.

Therefore, the main finding from this network is not thematic diversity, but thematic concentration. The subcorpus appears as a specialised body of literature centred on the use of data science and machine learning to support hotel revenue management decisions. This reveals a mismatch between the broader intention of the search string, which included reports, dashboards and key performance indicators, and the strongest thematic signal retrieved, which is concentrated on revenue-management decision support rather than on artificial intelligence-supported critical interpretation of hotel accounting information.

4.2.2. Thematic Map: Positioning of Decision Support, Accounting Information Systems and Reporting Themes

This subsection analyses the thematic positioning of the reporting and decision support subcorpus according to centrality and density, assessing whether the identified themes appear as motor, basic, niche, or emerging or declining themes.

As shown in Figure 5, the thematic map for this subcorpus shows a very limited and weakly differentiated structure. All themes are positioned close to the centrality axis, which indicates that the subcorpus does not clearly separate into distinct motor, basic, niche, or emerging/declining themes.

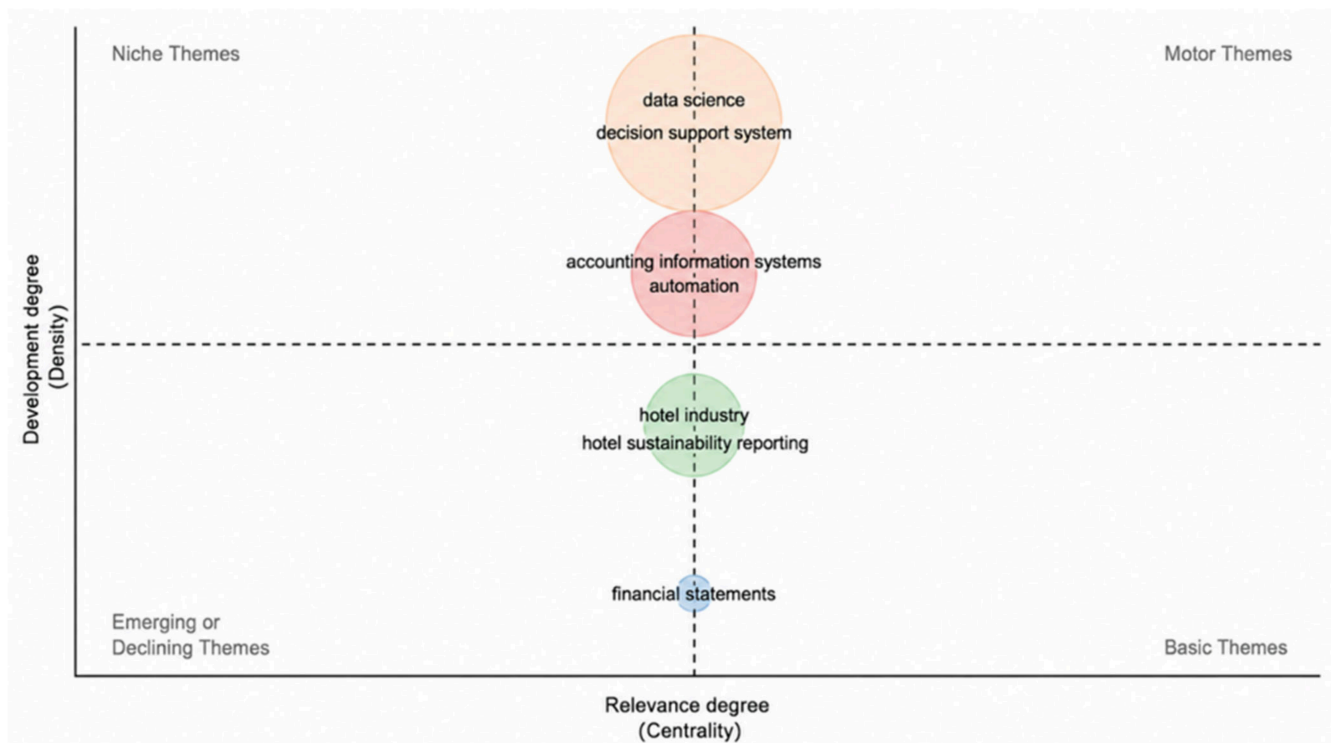


Figure 5. Thematic map of decision support, accounting information systems and reporting themes.

The most developed theme is data science/decision support system, positioned in the upper part of the map. This suggests that decision support based on data science is the strongest thematic area in this subcorpus, although its central position indicates that it is not clearly differentiated as a dominant motor theme. This theme is mainly supported by [Saitta et al. \(2024, 2026\)](#), whose abstracts focus on dynamic price prediction in hotel revenue management systems and describe data science and machine learning as tools for supporting revenue managers' decisions. [Ibrahim and Handayani \(2022\)](#) provide complementary support, as their review discusses BI frameworks, data visualisation and decision-making in tourism organisations. [Han \(2025\)](#) also supports the broader data-driven performance logic but should be read as complementary rather than central to this theme.

Accounting information systems/automation also appears above the density threshold, suggesting a relatively developed but still narrow research line. This theme is corroborated by [Zayed et al. \(2024\)](#), who examine the role of artificial intelligence (AI) in accounting information systems (AIS) for fraud detection, automation, accurate reporting and predictive analysis. [Diavastis \(2024\)](#) also supports this theme by linking management accounting practices, AIS, information quality and hotel performance. [Anggraeni and Winarningsih \(2021\)](#) reinforce the same line by connecting AIS quality with financial performance. Together, these studies show that AIS and automation are visible in the map, but mostly through information quality, efficiency, reporting accuracy and performance effects.

Below the threshold, hotel industry/hotel sustainability reporting and financial statements appear as less developed themes. The sustainability reporting theme is supported by [Al-Wattar et al. \(2019\)](#), who examine the integration of hotel sustainability reporting practices into AIS, and by [Khaghaany et al. \(2019\)](#), who analyse the value relevance of

sustainability reporting in tourism companies' annual reports. These studies confirm the presence of reporting concerns, but their position below the density threshold suggests that this theme remains weakly integrated with the broader decision support structure.

The financial statement's theme is supported by Saleh et al. (2021), Pavone et al. (2023), and Ribarić Čučković (2020). Saleh et al. (2021) are particularly relevant because they connect AI with the consistency and interpretation of financial statements in classified hotels. Pavone et al. (2023) support the theme through a quantitative analysis of financial statements in hospitality, while Ribarić Čučković (2020) links quality cost accounting with management information in the hospitality industry. These studies confirm that financial statements are present in the corpus, but mainly as objects of reporting, performance assessment and accounting analysis.

Overall, this subcorpus is characterised by thematic concentration rather than diversity. The thematic map adds nuance to the keyword co-occurrence network by showing that, beyond data-driven decision support, the corpus also includes accounting information systems (AIS), automation, sustainability reporting and financial statements. However, these themes remain weakly differentiated, only partially connected and insufficiently integrated as a coherent research structure. Within this subcorpus, the thematic structure is stronger around decision support, automation, reporting quality and financial statement analysis than around dashboard-based judgement, anomaly detection or critical reading of accounting information.

4.2.3. Qualitative Reading: How Reporting and Decision-Support Outputs Are Framed

This subsection qualitatively examines how the 25 documents frame reports, dashboards, key performance indicators and decision-support outputs. The analysis assesses whether these artefacts are treated mainly as tools for monitoring, visualisation, automation and decision support, or whether they are also discussed as supports for anomaly detection, critical interpretation and human judgement.

The qualitative reading confirms that the subcorpus is more strongly oriented towards monitoring, automation, reporting reliability and operational decision support than towards critical interpretation or human judgement. Although the search strategy included reports, dashboards and key performance indicators, the documents retrieved do not form a consolidated body of literature on dashboards as interpretive artefacts. Instead, they bring together adjacent but only partially connected lines of research.

The first line concerns operational monitoring and decision support. Saitta et al. (2024, 2026) are central here because their studies frame data science and machine learning as tools for hotel dynamic pricing and revenue management decisions. In these works, key performance indicators are treated mainly as inputs for monitoring market conditions, future demand and pricing decisions. Ibrahim and Handayani (2022) support this decision-oriented reading from a broader BI perspective, while Han (2025) extends the same data-driven logic to cost control and performance evaluation in tourist hotels. These studies corroborate the finding that decision support is present, but mainly as operational and performance-oriented support.

The second line concerns automation, AIS and reporting reliability. Zayed et al. (2024) connect AI with AIS, fraud detection, automation, accurate reporting and predictive analysis. Diavastis (2024) links AIS with management accounting practices, information quality and hotel performance, while Anggraeni and Winarningsih (2021) connect AIS quality with financial performance. These studies show that technology is framed as a way to improve information production, reliability and managerial usefulness. However, they do not develop the interpretive process through which users critically read, compare or question reporting outputs.

The third line concerns reporting, sustainability reporting and financial statements. Al-Wattar et al. (2019) and Khaghaany et al. (2019) support the presence of sustainability reporting and AIS in the corpus. Saleh et al. (2021) are particularly relevant because they explicitly connect AI with the consistency and interpretation of financial statements in classified hotels. Pavone et al. (2023) also support the financial-statement theme through a quantitative approach to hospitality financial statements, while Ribarić Čučković (2020) links quality cost accounting with management information in hospitality. These studies confirm that reporting and financial statements are present, but mainly as objects of accounting analysis, performance assessment or reporting quality.

A smaller group of studies broadens the corpus towards data analytics and performance signals. Xie and So (2018) connect online reviews, managerial responses and hotel financial performance through data analytics, while Grandhi et al. (2021) discuss data-driven marketing, metrics and dashboards in relation to growth and profitability. These contributions are useful because they show how data, metrics and dashboards can inform managerial action, but they remain peripheral to the specific problem of hotel accounting interpretation.

Overall, the qualitative reading shows that the corpus contains several relevant components for the research problem of this paper: dynamic pricing, key performance indicators, BI, AIS, automation, reporting quality, sustainability reporting and financial statements. However, these components remain fragmented. The literature provides limited evidence of an integrated approach in which AI supports the critical reading of hotel accounting reports, dashboards or key performance indicators while preserving human judgement. More specifically, the abstracts offer little direct evidence on dashboard-based judgement, weak interpretations, omissions, anomaly interpretation or human validation of AI-supported recommendations. The main gap therefore lies not in decision support itself, but in its integration with the critical interpretation of accounting and performance information in hotel contexts.

4.3. Human Judgement, Interpretation and Critical Reading in Hotel Accounting Information

This section examines Stream 3, which corresponds to the subcorpus focused on human judgement, interpretation and critical reading in relation to hotel accounting and performance information. It is organised into three complementary analytical steps. First, Section 4.3.1 addresses Objective 1 by examining the Author Keyword co-occurrence network. Second, Section 4.3.2 addresses Objective 2 by analysing the thematic map according to centrality and density. Third, Section 4.3.3 addresses Objective 4 by interpreting whether the literature moves from accounting and performance information towards human judgement, critical interpretation and decision-making.

4.3.1. Keyword Co-Occurrence Network: Decision-Making, Accounting and Revenue Management Structures

This subsection examines the author keyword co-occurrence network for Stream 3 in order to identify how decision-making, accounting and revenue-management themes are structurally connected within the human interpretive subcorpus.

As shown in Figure 6, the keyword co-occurrence network for Stream 3 reveals three thematic clusters. The dominant structure is clearly organised around revenue management, which is the most central and influential node in the map (betweenness = 140.500; closeness = 0.033; PageRank = 0.211). This confirms that the subcorpus is strongly anchored in revenue-related research, particularly around hotel pricing, forecasting and performance-oriented decision-making.

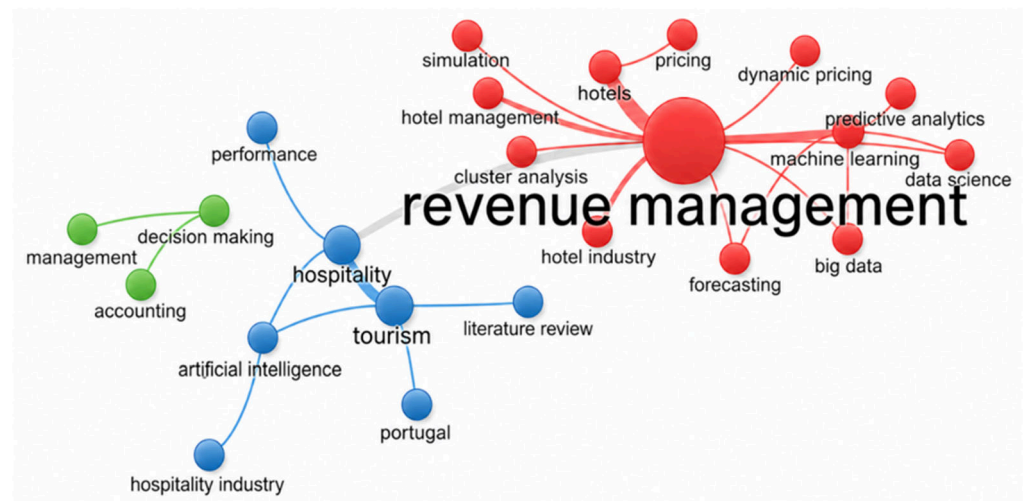


Figure 6. Keyword co-occurrence network of decision-making, accounting and revenue management themes.

In Cluster 1, revenue management is connected with terms such as machine learning (betweenness = 19.500; PageRank = 0.083), hotels (betweenness = 18.000; PageRank = 0.052), dynamic pricing, forecasting, predictive analytics, big data, data science, pricing, simulation and cluster analysis. This cluster indicates a strong operational and analytical orientation, where algorithmic and data-driven techniques are used to support revenue management decisions in hotel contexts. This pattern is directly supported by [António et al. \(2019\)](#), who connect big data, machine learning and decision-support systems with hotel booking cancellation prediction, and by [Egan and Haynes \(2019\)](#), who examine managers' perceptions of big data reliability in hotel revenue management decision-making. [Kocourek et al. \(2025\)](#) further support this cluster by analysing the factors shaping revenue management decision-making in small and medium-sized hospitality enterprises. Although several nodes have zero betweenness, their presence reinforces the technical vocabulary of the cluster.

Cluster 2 is centred on hospitality and tourism. Hospitality has the strongest bridging role in this cluster (betweenness = 83.000; closeness = 0.028; PageRank = 0.087), followed by tourism (betweenness = 35.000; PageRank = 0.079) and artificial intelligence (AI) (betweenness = 18.000; PageRank = 0.050). This suggests that hospitality functions as an important connector between the revenue management cluster and broader tourism-related themes. The presence of AI, performance, literature review, Portugal and hospitality industry shows that this cluster links technological and managerial discussions with the wider tourism and hospitality field. However, this cluster does not yet show a strong connection with accounting interpretation or human judgement. It mainly broadens the sectoral and technological context of the network, rather than shifting its centre away from revenue-management and performance-oriented decision-making.

Cluster 3 is smaller and more peripheral, composed of decision making, accounting and management. Within this cluster, decision-making is the only term with a bridging role (betweenness = 1.000; closeness = 0.500; PageRank = 0.063), while accounting and management have lower influence (betweenness = 0.000; closeness = 0.333; PageRank = 0.033). This indicates that accounting and management appear in the network but remain weakly connected to the dominant revenue management and hospitality structures. This peripheral position is consistent with [Downie \(1997\)](#), who examines the use of accounting information in hotel marketing decisions, [Anorue et al. \(2025\)](#), who analyse the influence of cost accounting information on management decision-making in hotel services, and [Diavastis \(2024\)](#), who links management accounting practices, accounting information systems and hotel performance. These studies confirm that accounting information is

relevant to decision-making, but the network shows that this line remains less central than the revenue management cluster.

The structure of Stream 3 is dominated by revenue management, with a second cluster linking hospitality, tourism and AI and a smaller peripheral cluster related to decision making, accounting and management. This result is important because the stream was designed to capture the broader contextual literature on human judgement, interpretation and critical reading, yet the strongest network structure still revolves around revenue management, pricing, forecasting and data-driven hotel performance. Accounting and decision-making concepts are present, but they do not yet form the central organising structure of the subcorpus.

4.3.2. Thematic Map: Positioning of Human Interpretive Themes

This subsection analyses the thematic map of Stream 3 to assess how accounting, decision-making and interpretive themes are positioned in terms of centrality and density.

As shown in Figure 7, the thematic map for Stream 3 shows a more diversified structure than Stream 2, with themes distributed across the four quadrants. In the Motor Themes quadrant, the main themes are machine learning/big data and decision-making/accounting. Their position indicates that these topics are both relevant and relatively well developed within this subcorpus. This suggests that the literature connects data-driven methods with accounting and decision-making issues, although still within a broader managerial and analytical framing. The machine learning/big data theme is directly supported by [António et al. \(2019\)](#), who link big data and machine learning-based decision support with hotel booking cancellation prediction, and by [Egan and Haynes \(2019\)](#), who examine the perceived reliability of big data in hotel revenue management decision-making. The decision-making/accounting theme is supported by [Downie \(1997\)](#), [Anorue et al. \(2025\)](#), and [Diavastis \(2024\)](#), whose studies connect accounting information, cost accounting and management accounting practices with managerial decision-making in hotel contexts.

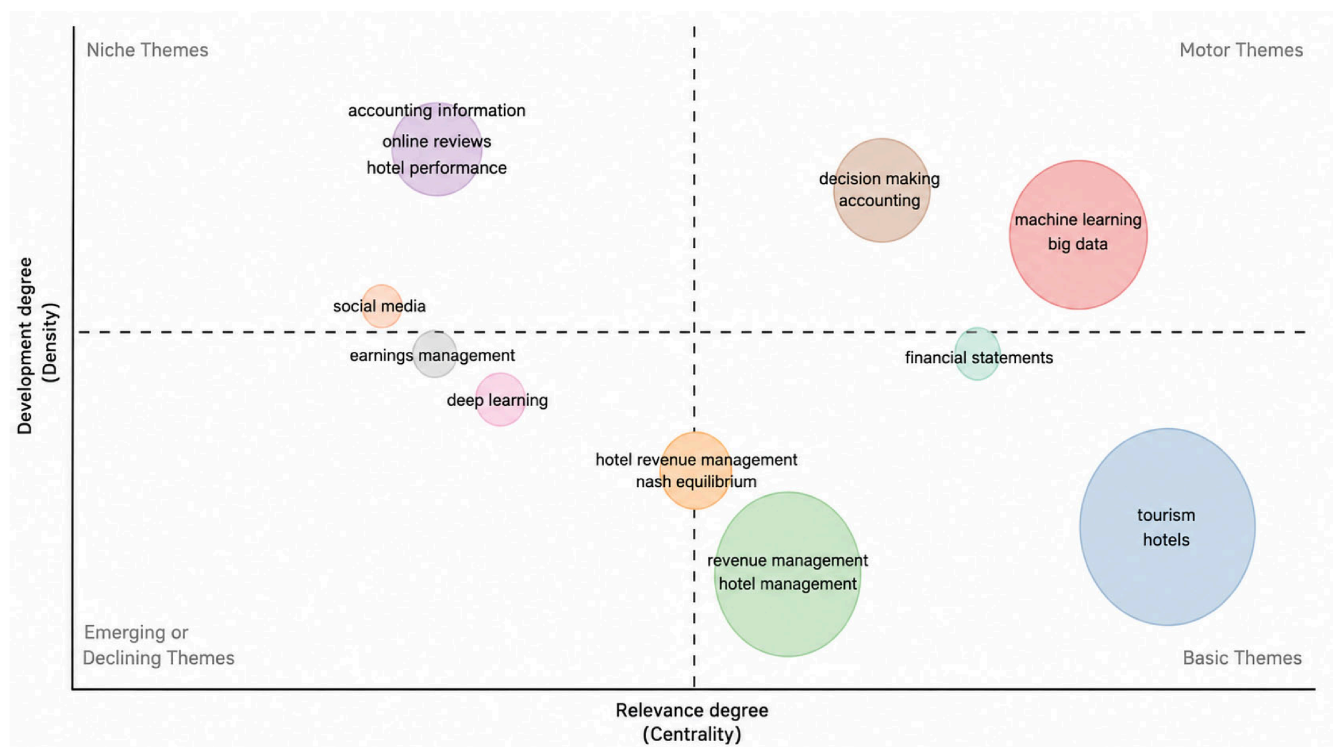


Figure 7. Thematic map of accounting, decision-making and interpretive themes in Stream 3.

In the Basic Themes quadrant, tourism/hotels appear as the most central theme, with a large bubble size, indicating its strong relevance to the corpus. However, its lower density suggests that it functions more as a broad foundational theme than as a highly specialised research line. The theme revenue management/hotel management is also positioned in the lower-right area, showing relevance to the corpus but with lower internal development. Financial statements appear close to the central boundary, suggesting a transversal but not strongly developed topic. This configuration is consistent with the overall structure of the stream, in which hotel and tourism contexts provide the broad setting, while revenue management concerns remain highly visible. The financial statements theme is most clearly supported by [Saleh et al. \(2021\)](#), who connect artificial intelligence with the consistency and interpretation of financial statements in classified hotels.

The Niche Themes quadrant includes accounting information/online reviews/hotel performance, positioned in the upper-left area. This indicates a theme with some internal development, but lower centrality in the overall structure of the subcorpus. Social media also appears near the boundary between niche and emerging/declining areas, suggesting a more limited and peripheral role. This niche configuration is supported by [Gallo et al. \(2018\)](#), who link dashboards and neural networks with hotel management forecasting, and by [Nicolau et al. \(2024\)](#), who connect online review sentiment with hotel performance. These studies show that information signals, performance indicators and review-based evidence are present, but they do not occupy a central place in the overall structure of the stream.

In the Emerging or Declining Themes quadrant, the map includes earnings management, deep learning and hotel revenue management/Nash equilibrium. These themes show lower density and lower centrality, indicating that they are either still emerging, weakly consolidated, or less connected to the dominant structure of the stream. Their position suggests that these lines have not yet developed into central areas of literature, even though they point to potentially relevant extensions of the field.

Overall, Stream 3 presents a broader thematic configuration than Stream 2. The map highlights tourism/hotels as the main basic theme, machine learning/big data and decision-making/accounting as the most developed and central themes, and a set of more peripheral topics related to accounting information, online reviews, hotel performance, earnings management, deep learning and Nash equilibrium. This pattern shows that Stream 3 is more directly connected to accounting and decision-making than the previous streams. Even so, the thematic structure still leans more strongly towards hotel management, revenue-related concerns and data-driven decision support than towards a fully developed literature on critical reading, sensemaking or human judgement in accounting contexts.

4.3.3. Interpretive Synthesis: From Accounting Information to Human Judgement

This subsection synthesises the keyword co-occurrence network and the thematic map to assess whether Stream 3 moves beyond accounting and performance information towards interpretation, professional judgement and critical decision-making.

The evidence from Stream 3 shows a more explicit connection with accounting information and decision-making than the previous two streams. Studies such as [Downie \(1997\)](#), [Anorue et al. \(2025\)](#), and [Diavastis \(2024\)](#) confirm that accounting information, cost accounting and management accounting practices are used to support managerial decisions in hotel contexts. [Saleh et al. \(2021\)](#) also move closer to the core concern of this paper by connecting artificial intelligence with the consistency and interpretation of financial statements in classified hotels.

However, this movement from accounting information to interpretation remains incomplete. The dominant network structure and several themes in the map continue to be

shaped by revenue management, pricing, forecasting and hotel performance. [António et al. \(2019\)](#), [Egan and Haynes \(2019\)](#), and [Kocourek et al. \(2025\)](#) show that decision-making is strongly present, but mainly in relation to revenue-management decisions, data reliability, booking behaviour and performance-oriented managerial action.

The clearest evidence of human judgement appears in studies that examine the limits of automated or algorithmic decision support. [Bendoly \(2013\)](#) addresses the tension between imperfect judgement and imperfect prescription in hospitality booking behaviour, while [Mohammed and Denizci Guillet \(2025\)](#) examine heuristics, biases, human–algorithm interaction and override decision-making in hotel revenue management. These studies are particularly important because they show that human judgement is not absent from the corpus. Yet it appears mainly in relation to pricing and revenue management decisions, rather than as part of a broader literature on accounting report interpretation, dashboard-based judgement or critical reading of financial and performance information.

Stream 3 therefore provides the clearest contextual view of the human interpretive dimension among the three subcorpora, but direct evidence of AI-supported human judgement remains limited. The literature includes accounting information, management decision-making, financial statements, dashboards, online review signals and human–algorithm interaction. However, these elements are not yet integrated into a coherent research line on how managers critically read accounting reports, interpret dashboards, identify weak signals or validate artificial intelligence-supported recommendations. The connection between accounting information and human judgement is therefore visible but remains fragmented, particularly when AI-supported interpretation is considered.

4.4. Cross-Stream Comparison: Technological, Reporting and Human Interpretive Dimensions

This section compares the three subcorpora in order to identify thematic convergences, divergences and underexplored intersections across the technological, reporting and human interpretive dimensions of the literature. It addresses Objectives 3 and 4 by bringing together the results of the keyword co-occurrence networks, thematic maps and qualitative interpretation developed in Sections 4.1–4.3.

4.4.1. Thematic Convergences: Analytics, Performance and Decision Support

The comparison across the three streams shows that the strongest convergence is around analytics, performance and decision support, rather than around accounting interpretation or human judgement. This conclusion is grounded in the bibliometric and interpretive results presented in Sections 4.1–4.3. As summarised in Table 1, all three subcorpora include decision-oriented analytical themes, but these themes are developed mainly through forecasting, pricing, revenue management, automation, information quality and performance monitoring.

Revenue management is highly visible across the three subcorpora, although this recurrence should be interpreted in light of its inclusion in the search strategy for each stream. Its position is therefore considered within each subcorpus rather than as evidence of its prevalence across the wider field. In Stream 1, it is strongly connected to predictive and operational applications; in Stream 2, to focused decision-support concerns; and in Stream 3, it forms the dominant network core. Performance-related language also appears across the streams, although with different emphases: operational and financial performance in Stream 1, reporting and decision-support outputs in Stream 2, and hotel performance, accounting information and managerial decision-making in Stream 3.

Decision support is another important convergence, but it is mostly framed as operational, analytical or performance-oriented support. In the mapped literature, decision support is associated with forecasting, pricing, revenue management, information quality,

accounting information systems, dashboards, financial statements or accounting information. However, the outputs do not show a similarly strong convergence around critical reading, dashboard-based judgement, weak-signal interpretation or human validation of artificial intelligence-supported recommendations. The convergence is therefore real, but it is stronger around prediction, optimisation and operational control than around interpretation, judgement and reflective use of accounting information.

Table 1. Cross-stream thematic convergences in analytics, performance and decision support.

Stream	Main Convergent Themes	Central Supporting Studies	Interpretation of the Convergence
Stream 1: AI, BI and analytics in hotel accounting and performance management	Machine learning; revenue management; forecasting; optimisation; performance-oriented applications.	Pereira and Cerqueira (2022) ; António et al. (2019) ; Das et al. (2021) ; Brunato and Battiti (2020) .	The subcorpus is strongly structured around predictive analytics, demand forecasting, booking cancellation prediction, dynamic pricing and revenue management optimisation.
Stream 2: AI-supported reporting, KPIs and decision-support outputs	Data science; decision-support systems; dynamic pricing; hotel revenue management systems; accounting information systems; automation; financial statements.	Saitta et al. (2024, 2026) ; Zayed et al. (2024) ; Diavastis (2024) ; Saleh et al. (2021) .	The reporting-oriented corpus is narrower, but its strongest signal is still operational decision support. Reporting and accounting themes are present, although less integrated with critical interpretation or human judgement.
Stream 3: Human judgement, interpretation and critical reading	Revenue management; machine learning/big data; decision-making/accounting; hotel performance; accounting information.	António et al. (2019) ; Egan and Haynes (2019) ; Kocourek et al. (2025) ; Downie (1997) ; Anorue et al. (2025) ; Diavastis (2024) .	The human interpretive corpus comes closer to accounting and decision-making, but still remains strongly shaped by revenue management, performance-oriented decision support and data-driven managerial action.

4.4.2. Thematic Divergences: Fragmented Links Between Technology, Reporting and Human Judgement

The main divergence across the three streams is not the absence of technology, reporting or decision-making, but the fact that these dimensions develop unevenly and remain weakly integrated. Stream 1 presents the strongest technological concentration, with a strong focus on artificial intelligence, business intelligence, machine learning, predictive analytics, forecasting, dynamic pricing and revenue management. However, this concentration is mainly directed towards prediction and performance optimisation, rather than towards accounting report interpretation, dashboard-based judgement or human validation of decision-support outputs.

Stream 2 occupies the most specific but also the least consolidated position. It was designed to capture the intersection between artificial intelligence-supported reporting, key performance indicators, dashboards and decision-support systems. Its smaller size reflects the narrower conceptual intersection defined by the search strategy and is interpreted cautiously rather than as evidence of the maturity of this research area. Although the corpus includes decision support, accounting information systems, automation, sustainability reporting and financial statements, the explicit integration of dashboards, accounting interpretation and human judgement remains limited.

As a contextual stream, Stream 3 provides a closer view of the human interpretive dimension, since it includes accounting information, decision-making, management accounting, financial statements, dashboards, online review signals and human–algorithm interaction. Nevertheless, its dominant structure is still shaped by revenue management,

hotel performance and data-driven decision-making. The clearest evidence of human judgement, particularly in Bendoly (2013) and Mohammed and Denizci Guillet (2025), remains mainly connected to revenue management and pricing decisions, rather than to accounting report interpretation or dashboard-based judgement.

These divergences show that the three dimensions of the paper are present in the literature, but they are not yet integrated into a coherent research line. The technological dimension is strongest in Stream 1, the reporting and dashboard dimension appears most explicitly but weakly in Stream 2, and the human interpretive dimension is most visible but still fragmented in Stream 3. The central problem is therefore not a lack of relevant literature, but a lack of integration between technology, reporting outputs and human judgement.

4.4.3. Underexplored Intersections: AI-Supported Critical Reading and Dashboard-Based Judgement

The cross-stream comparison shows that the main gap is not the absence of artificial intelligence (AI), analytics, reporting outputs or decision support. These elements are clearly present across the mapped literature. The gap lies in the limited integration between these elements and the human interpretation of accounting and performance information. Table 2 summarises the main underexplored intersections emerging from the comparison.

Table 2. Underexplored intersections identified across the three streams.

Underexplored Intersection	What the Review Shows	Why It Matters
AI-supported critical reading of accounting reports	AI and analytics are mainly used for prediction, automation, pricing and information quality.	There is limited evidence on how AI can help managers question accounting narratives or identify fragile interpretations.
Dashboard-based judgement	Dashboards and key performance indicators appear in the corpus, but mainly as monitoring or visualisation tools.	The literature says little about how managers interpret dashboards, compare indicators or validate what dashboards suggest.
Anomaly detection and weak-signal interpretation	Fraud detection, reporting reliability and performance monitoring are present, but mostly as technical concerns.	The interpretive reading of anomalies, omissions, inconsistencies or weak signals remains weakly integrated with the broader literature on decision support and accounting interpretation.
Human validation of AI-supported outputs	Human judgement appears more clearly in Stream 3, especially in relation to heuristics, biases and human–algorithm interaction.	This evidence is still mainly linked to revenue management and pricing decisions, not to accounting report interpretation.
Integration between technology, reporting and judgement	Stream 1 shows the strongest technological concentration, Stream 2 captures reporting outputs, and Stream 3 provides the contextual human judgement dimension.	These dimensions remain fragmented rather than forming a coherent research line.

This synthesis confirms the research gap that motivated the study: although AI, analytics, reporting outputs and decision support are present in the literature, they remain weakly integrated with critical interpretation, dashboard-based judgement and human validation in hotel accounting contexts. Reports, dashboards and key performance indicators can increase the visibility of accounting and performance information, but visibility does not necessarily lead to interpretation. The mapped literature still provides limited evidence on

how AI could support the identification of omissions, inconsistencies, anomalies or fragile performance narratives while preserving human judgement and professional responsibility.

4.5. Future Research Agenda: AI-Supported Critical Reading and Human Judgement in Hotel Accounting

This section addresses Objective 5 by translating the underexplored intersections identified in the cross-stream comparison into a focused future research agenda. The results show that artificial intelligence (AI), analytics, reporting outputs, dashboards, key performance indicators (KPIs), accounting information systems and decision support are already present in the literature. However, they remain weakly integrated with critical interpretation, professional judgement and the human validation of decision-support outputs.

The agenda proposed here is therefore not centred on AI as a replacement for accounting expertise. Rather, it positions AI as a potential support for more reflective, contextual and responsible interpretation of hotel accounting and performance information. Reports and dashboards organise information and make indicators more visible, but they do not determine their own meaning. Their value depends on how managers, accountants and decision-makers interpret relationships between revenues, costs, margins, operational pressures, customer signals and strategic assumptions.

Table 3 summarises the main future research lines emerging from this interpretation, linking each line to the rationale provided by the review and to possible research directions.

Table 3. Future research agenda for AI-supported critical reading and human judgement in hotel accounting.

Future Research Line	Rationale from the Review	Illustrative Research Focus
AI-supported critical reading of hotel accounting reports	The mapped literature is strong in prediction, automation and decision support, but shows limited integration with critical interpretation of accounting information.	How can AI help managers question accounting narratives, compare indicators and identify fragile or incomplete interpretations?
Report interpretation and contextual judgement	Financial statements, reporting quality and accounting information appear in the corpus, but they are rarely connected to situated managerial interpretation.	How do hotel managers interpret accounting and performance reports under uncertainty, and how can AI support rather than replace this process?
Anomaly detection and weak-signal identification	Fraud detection, performance monitoring and reporting reliability are present, but mostly as technical concerns.	How can AI identify inconsistencies, omissions, unexpected patterns or weak signals in hotel accounting and performance data?
Dashboard-based judgement and KPI interpretation	Dashboards and KPIs appear mainly as monitoring or visualisation tools, not as interpretive artefacts requiring validation.	How do decision-makers read dashboards, compare KPIs and detect misleading performance signals in hotel contexts?
Human validation of AI-supported recommendations	Human judgement appears most clearly in relation to revenue management, heuristics, biases and human–algorithm interaction.	How do accountants, managers and revenue specialists accept, reject, override or contextualise AI-supported recommendations?
Integration between technology, reporting and judgement	The three streams show that technology, reporting outputs and human judgement remain fragmented.	What integrated models can connect AI-supported technologies, accounting reports, dashboards and professional judgement in hotel accounting?

5. Conclusions

This study examined how research on artificial intelligence (AI), business intelligence (BI) and analytics in hotel accounting addresses report interpretation, decision support and human judgement. It combined a structured review with bibliometric science mapping and compared three complementary research streams to assess how technological developments relate to the interpretation of accounting information.

The retrieved literature shows a stronger thematic concentration in technological and operational applications than in the interpretation of accounting information. Machine learning, AI, revenue management, forecasting, dynamic pricing, optimisation and performance support are prominent themes within the mapped literature. Revenue management is particularly prominent and occupies a central position across the three bibliometric streams, although this recurrence partly reflects its inclusion in the search strategy of each stream. AI is therefore well represented in predictive analytics and operational decision support within the retrieved hospitality literature.

Research on the interpretation of accounting information is less strongly integrated with these technological and operational themes. Although the second stream focused on AI-supported reporting, dashboards, KPIs and decision-support outputs, the retrieved studies dealt mainly with data science, accounting information systems, automation, reporting quality and financial statements. The third stream provided a broader contextual view of human interpretation and judgement, including accounting information, decision-making, dashboards and human–algorithm interaction, but these themes remain dispersed and have not formed a coherent body of research on the critical interpretation of accounting information.

These findings support the research gap identified in the introduction. The main limitation of mapped literature is not a lack of AI applications, analytics or decision-support technologies, it is the weak conceptual connection between these technologies, reporting outputs and human interpretive judgement. Research now needs to examine how AI can support critical reading, contextual interpretation and responsible use of accounting information in managerial decisions, beyond prediction and operational performance.

5.1. Theoretical Implications

The study extends the way AI is conceptualised in hotel accounting. Research has treated it mainly as a technology for forecasting, automation and operational optimisation. The findings indicate that AI may also support the interpretation of accounting information and performance reports. This adds an interpretive dimension to a literature in which technological applications are more strongly represented.

The review also identifies a restricted understanding of decision support. Across the three bibliometric streams, decision support is associated mainly with forecasting, dynamic pricing, revenue management, reporting reliability and performance monitoring. Its role in contextual reasoning, professional judgement and the critical evaluation of accounting information has received far less attention.

The bibliometric evidence also indicates limited integration between AI-supported technologies, reporting and dashboard outputs, and human judgement. These areas appear only weakly connected in the mapped literature, even though hotel accounting decisions often depend on their interaction. The three-stream structure offers a way to examine these relationships within a shared analytical framework.

Dashboards and KPIs also require a broader conceptual treatment. They are usually presented as tools for visualisation and monitoring, but they may also function as interpretive artefacts through which users compare, validate and question accounting information or identify anomalies.

The theoretical issue is therefore not confined to what AI can predict or automate. It also concerns the conditions under which AI can support professional judgement, accountability, prudence and responsible managerial decision-making.

5.2. Practical Implications

The findings have practical implications for hospitality organisations, hotel managers, accountants, developers of AI-supported accounting systems, and those responsible for hospitality education and professional training.

Hotel managers and accountants should not treat dashboards and performance indicators as automatic representations of organisational performance. Greater access to data and improved monitoring do not remove the need for interpretation. Favourable indicators may coexist with weak profitability, inefficient cost structures, operational constraints or strategic risks. AI-generated outputs therefore need to be assessed against the wider operational and financial context.

Developers of AI-supported accounting systems should design these tools to support critical reasoning, not simply to produce predictions or recommendations. Decision-support systems could explain how outputs were generated, identify inconsistencies and omitted information, and detect weak signals that require managerial attention. These functions would allow users to examine the basis of automated recommendations rather than accept them without scrutiny.

Human validation remains necessary when AI is used for forecasting, pricing, reporting or performance monitoring. Hotel managers and accounting professionals retain responsibility for contextualising accounting information, evaluating trade-offs and recognising organisational conditions that may not be represented in the system.

5.3. Limitations and Future Research

This study has some limitations. First, the bibliometric analysis was based solely on the Scopus database. Although Scopus offers broad coverage of high-quality research, relevant studies indexed elsewhere may not have been included. Second, the review followed a predefined search strategy, which may have omitted studies using alternative terminology or produced different thematic emphases under alternative search formulations. A supplementary search-sensitivity check using contemporary AI terminology did not materially alter the main interpretation of the review. The findings should therefore be interpreted in relation to the retrieved subcorpora rather than as exhaustive representations of the wider field. Finally, the analysis focused on bibliometric mapping and qualitative interpretation rather than on assessing the practical effectiveness of AI-supported accounting systems in organisational settings.

These limitations also suggest opportunities for future research. Further studies could examine how AI supports the interpretation of accounting information through explainable AI, anomaly detection and contextual reasoning. Additional research should also explore how accountants, controllers and hotel managers combine AI-generated insights with professional judgement in decision-making. Finally, greater integration between accounting, hospitality management, information systems and organisational behaviour would contribute to the development of more human-centred AI frameworks that combine computational capabilities with managerial expertise.

5.4. Final Remarks

The digital disruption transforming hotel accounting is no longer defined simply by the adoption of artificial intelligence, advanced analytics or increasingly sophisticated decision-support technologies. Rather, the findings of this review suggest that the next stage of digital transformation will depend on the ability to integrate these technological

advances with the critical interpretation of accounting information and the professional judgement of decision-makers.

Rather than replacing accountants and managers, AI has the potential to augment their analytical capabilities by supporting the identification of anomalies, strengthening contextual interpretation and improving the quality of managerial reasoning. However, achieving this objective requires a shift from technology-centred approaches towards human-centred decision-support systems in which transparency, explainability and professional accountability become fundamental design principles.

Ultimately, the impact of digital disruption on hospitality accounting should not be measured solely by improvements in forecasting accuracy or operational efficiency. Its greatest contribution will be realised when intelligent systems support critical thinking, informed interpretation and responsible managerial judgement, enabling hospitality organisations to make more transparent, resilient and sustainable accounting and financial decisions.

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Appendix A. Search Strategy, Query Construction and Filtering Criteria

The search strategy was organised into three complementary streams. Each stream was built to address one dimension of the review: the technological and analytical dimension, the reporting and dashboard dimension, and the human interpretive dimension. All searches were conducted in Scopus on 24 May 2026 using the TITLE-ABS-KEY field.

Stream 1 was developed to identify the broader literature on artificial intelligence, business intelligence and analytics in hotel accounting and performance management. Stream 2 was developed to capture the more specific intersection between AI-supported technologies and the reporting or dashboard-based presentation of accounting and performance information. Stream 3 was developed as a contextual stream capturing the broader human interpretive dimension of accounting and performance information, including interpretation, comprehension, sensemaking, critical reading, decision-making and professional judgement.

The complete search strings used in Scopus, together with the conceptual focus and final corpus size of each stream, are presented in Table A1.

Table A1. Three-stream search strategy used in Scopus.

Stream	Focus of the Stream	Scopus Query	Final Corpus
Stream 1	AI, BI and analytics in hotel accounting and performance management	(hotel* OR hospitalit* OR lodging OR accommodation OR resort*) AND (accounting OR "hotel accounting" OR "hospitality accounting" OR "management accounting" OR "managerial accounting" OR "cost accounting" OR budgeting OR budget* OR "financial performance" OR "performance measurement" OR "performance management" OR KPI* OR "key performance indicator*" OR "revenue management" OR RevPAR OR GOPPAR OR EBITDA OR "food cost" OR "labour cost") AND ("artificial intelligence" OR "machine learning" OR "business intelligence" OR "data analytics" OR "predictive analytics").	255
Stream 2	AI-supported reporting, dashboards, KPIs and decision support	(hotel* OR hospitalit* OR lodging OR accommodation OR resort*) AND (dashboard* OR report* OR "management report*" OR "financial report*" OR "financial statement*" OR "performance report*" OR "balanced scorecard" OR KPI* OR "performance indicator*" OR "key performance indicator*") AND ("financial performance" OR "cost control" OR "revenue management" OR profitability OR RevPAR OR GOPPAR OR EBITDA OR "management accounting" OR "managerial accounting" OR accounting) AND ("artificial intelligence" OR "machine learning" OR "business intelligence" OR "data analytics" OR "predictive analytics" OR "decision support system*")	25
Stream 3	Human judgement, interpretation and critical reading of accounting and performance information	(hotel* OR hospitalit* OR lodging OR accommodation OR resort*) AND (accounting OR "hotel accounting" OR "hospitality accounting" OR "management accounting" OR "managerial accounting" OR "financial report*" OR "management report*" OR dashboard* OR KPI* OR "performance indicator*" OR "key performance indicator*" OR "revenue management" OR "financial performance") AND (interpretation OR comprehension OR sensemaking OR "critical reading" OR "analytical reading" OR "decision making" OR decision-making OR "managerial decision*" OR "human judgement" OR judgment OR "professional judgement" OR "human-AI collaboration")	310

Note. AI = artificial intelligence; BI = business intelligence; KPI = key performance indicator. All searches were conducted in Scopus on 24 May 2026 using the TITLE-ABS-KEY field.

The strings were constructed from conceptual blocks. In all three streams, the first block delimited the sectoral context through terms such as hotel, hospitality, lodging, accommodation and resort. The remaining blocks were adapted to the specific purpose of each stream.

For Stream 1, the second block captured the accounting and performance-management domain, including accounting, management accounting, cost accounting, budgeting, financial performance, performance measurement, KPIs, revenue management, RevPAR, GOPPAR, EBITDA, food cost and labour cost. The third block captured the analytical technology dimension through terms such as artificial intelligence, machine learning, business intelligence, data analytics and predictive analytics. This combination was used to ensure

that the retrieved documents addressed the intersection between analytical technologies, hotel accounting and performance management.

For Stream 2, the string added a stronger focus on reporting and dashboard-related terms, including dashboard, report, management report, financial report, financial statement, performance report, balanced scorecard, KPI and performance indicator. These terms were combined with financial and accounting terms, and with AI, analytics and decision-support terms. This stream therefore focused less on the broad adoption of analytical technologies and more on the mechanisms through which accounting and performance information is transformed into reports, dashboards, indicators and decision-support outputs. Preliminary testing showed that when the reporting-related block was combined with the AI, business intelligence, analytics and decision-support block, the corpus was reduced to 25 documents. The resulting corpus was retained because it captured the explicitly defined intersection targeted by Stream 2. Its smaller size was not interpreted as evidence that AI-supported reporting constitutes an emerging field, but as a consequence of the more specific combination of concepts required by this search stream.

For Stream 3, the string focused on the human interpretive dimension. It combined accounting, reporting and performance-information terms with interpretation, comprehension, sensemaking, critical reading, analytical reading, decision-making, managerial decision-making, human judgement, professional judgement and human-AI collaboration. Unlike Streams 1 and 2, Stream 3 did not require explicit AI or analytics terminology. This decision allowed the review to capture the broader contextual literature on human interpretation and judgement in relation to accounting and performance information. Stream 3 was therefore used to establish the human-judgement dimension for comparison with the AI-related streams, rather than being interpreted as direct evidence of AI-supported human judgement.

The same filtering logic was applied across the three streams to ensure methodological consistency. The subject areas retained were Computer Science; Business, Management and Accounting; Engineering; Economics, Econometrics and Finance; Social Sciences; Mathematics; and Decision Sciences. These areas were retained because they were aligned with the technological, managerial, accounting, financial and decision-support dimensions of the review.

Subject areas with no substantive connection to hotel accounting, financial performance, analytics, reporting, interpretation or decision support were excluded. These included Medicine; Physics and Astronomy; Psychology; Multidisciplinary; Earth and Planetary Sciences; Arts and Humanities; Agricultural and Biological Sciences; Materials Science; Chemical Engineering; Neuroscience; Health Professions; and Biochemistry, Genetics and Molecular Biology.

The review retained articles, reviews, conference papers and book chapters. Articles and reviews were retained as core academic outputs. Conference papers were retained because research on artificial intelligence, business intelligence, analytics, decision support and information systems is often disseminated through conference proceedings. Book chapters were retained because they may provide relevant conceptual, applied or interdisciplinary contributions. Conference reviews, books, notes, data papers and retracted documents were excluded to preserve comparability, analytical reliability and scientific quality.

Only documents written in English were retained. This criterion was applied to ensure consistency in bibliometric processing and interpretive analysis, particularly because the science-mapping stage required comparison of titles, abstracts, keywords and thematic structures across documents.

The final corpus obtained after filtering is summarised in Table A2.

Table A2. Final corpus and type of analysis by stream.

Stream	Final Corpus	Type of Analysis
Stream 1	255	Bibliometric science mapping
Stream 2	25	Exploratory bibliometric mapping and qualitative reading
Stream 3	310	Bibliometric science mapping

Stream 1 and Stream 3 produced corpora suitable for bibliometric science mapping. Stream 2 produced a smaller but conceptually focused corpus. It was therefore analysed in Bibliometrix/Biblioshiny for consistency with the overall review design, but the outputs were interpreted cautiously and complemented by qualitative reading.

References

- Abbas, K. (2026). Management accounting and artificial intelligence: A comprehensive literature review and recommendations for future research. *The British Accounting Review*, 58, 101551. [\[CrossRef\]](#)
- Al-Wattar, Y. M. A., Almagtome, A. H., & Al-Shafeay, K. M. (2019). The role of integrating hotel sustainability reporting practices into an accounting information system to enhance hotel financial performance: Evidence from Iraq. *African Journal of Hospitality, Tourism and Leisure*, 8(5), 1–16.
- An, M., Mehrvarz, M., Stamper, J., & McLaren, B. M. (2026). Revisiting the hint button: Consistent negative associations between unproductive hint use and learning outcomes in intelligent tutoring systems. In *Proceedings of the 16th international learning analytics and knowledge conference (LAK 2026)* (pp. 150–159). Association for Computing Machinery. [\[CrossRef\]](#)
- An, R., Zhu, W., Zhao, Q., Laaksonen, A., & Lan, S. (2026). From literature to research-based learning: An AI-powered information extraction system to enhance undergraduate thesis completion. *Computers and Education: Artificial Intelligence*, 10, 100591. [\[CrossRef\]](#)
- Anggraeni, A. F., & Winarningsih, S. (2021). The effects of accounting information system quality on financial performance. *Economic Annals-XXI*, 193(9–10), 128–133. [\[CrossRef\]](#)
- Anorue, H. C., Ugwoke, E. O., & Okanazu, O. O. (2025). Influence of cost accounting information on management decision making of hotel services in South East, Nigeria. *International Journal of Services and Operations Management*, 51(3), 337–357. [\[CrossRef\]](#)
- António, N., de Almeida, A., & Nunes, L. (2019). Big data in hotel revenue management: Exploring cancellation drivers to gain insights into booking cancellation behavior. *Cornell Hospitality Quarterly*, 60(4), 298–319. [\[CrossRef\]](#)
- Bagherzadeh, S., Shokouhyar, S., Jahani, H., & Sigala, M. (2021). A generalizable sentiment analysis method for creating a hotel dictionary: Using big data on tripadvisor hotel reviews. *Journal of Hospitality and Tourism Technology*, 12(2), 210–238. [\[CrossRef\]](#)
- Bendoly, E. (2013). Real-time feedback and booking behavior in the hospitality industry: Moderating the balance between imperfect judgment and imperfect prescription. *Journal of Operations Management*, 31(1–2), 62–71. [\[CrossRef\]](#)
- Bhuiyan, M., Rahman, M. A., Hoque, A. B., Ashrafuzzaman, M., & Rahman, A. (2023). Advanced analytics and machine learning for revenue optimization in the hospitality industry: A comprehensive review of frameworks. *American Journal of Scholarly Research and Innovation*, 2(2), 52–74. [\[CrossRef\]](#)
- Binesh, F., Belarmino, A., van der Rest, J., Singh, A., & Raab, C. (2024). Forecasting hotel room prices when entering turbulent times: A game-theoretic artificial neural network model. *International Journal of Contemporary Hospitality Management*, 36(4), 1044–1065. [\[CrossRef\]](#)
- Brunato, M., & Battiti, R. (2020). Combining intelligent heuristics with simulators in hotel revenue management. *Annals of Mathematics and Artificial Intelligence*, 88(1–3), 71–90. [\[CrossRef\]](#)
- Buhalis, D., & Leung, R. (2018). Smart hospitality—Interconnectivity and interoperability towards an ecosystem. *International Journal of Hospitality Management*, 71, 41–50. [\[CrossRef\]](#)
- Cardoso, L., Araújo, A., Silva, R., de Almeida, G. G. F., Campos, F., & Lima Santos, L. (2024). Demystifying neurotourism: An interdisciplinary approach and research agenda. *European Journal of Tourism Research*, 36, 3618. [\[CrossRef\]](#)
- Cardoso, L., Araújo, A. F., Lima Santos, L., Schegg, R., Breda, Z., & Costa, C. (2021). Country performance analysis of Swiss tourism, leisure and hospitality management research. *Sustainability*, 13(4), 2378. [\[CrossRef\]](#)
- Cardoso, L., El Archi, Y., Moutinho, L., Almeida, P., & Benbba, B. (2025). Mind mapping the tourism destination choice framework: A theory-based perspective. *European Journal of Tourism Research*, 41, 4108. [\[CrossRef\]](#)
- Cardoso, L., Silva, R., Almeida, G., & Lima Santos, L. (2020). A bibliometric model to analyse country research performance: SciVal Topic Prominence approach in tourism, leisure and hospitality. *Sustainability*, 12(23), 9897. [\[CrossRef\]](#)
- Carneiro, T., Picoto, W. N., & Pinto, I. (2023). Big data analytics and firm performance in the hotel sector. *Tourism and Hospitality*, 4(2), 244–256. [\[CrossRef\]](#)

- Chen, C. (2017). Science mapping: A systematic review of the literature. *Journal of Data and Information Science*, 2(2), 1–40. [CrossRef]
- Cobo, M. J., López-Herrera, A. G., Herrera-Viedma, E., & Herrera, F. (2011). Science mapping software tools: Review, analysis, and cooperative study among tools. *Journal of the American Society for Information Science and Technology*, 62(7), 1382–1402. [CrossRef]
- Das, R., Chadha, H., & Banerjee, B. (2021). Multi-layered market forecast framework for hotel revenue management by continuously learning market dynamics. *Journal of Revenue and Pricing Management*, 20(3), 351–367. [CrossRef]
- Degn, L., Mejlgaard, N., & Schneider, J. W. (2019). Using mixed methods to map vaguely defined research areas. *Research Evaluation*, 28(4), 394–404. [CrossRef]
- Diavastis, I. (2024). Exploring the intersection of contemporary management accounting practices and accounting information systems: The impact on hotel performance. *Journal of Risk and Financial Management*, 17(11), 516. [CrossRef]
- Dogru, T., Line, N., & Mody, M. (2025). Generative artificial intelligence in the hospitality and tourism industry: Developing a framework for future research. *Journal of Hospitality and Tourism Research*, 49(2), 235–253. [CrossRef]
- Downie, N. (1997). The use of accounting information in hotel marketing decisions. *International Journal of Hospitality Management*, 16(3), 305–312. [CrossRef]
- Egan, D., & Haynes, N. C. (2019). Manager perceptions of big data reliability in hotel revenue management decision making. *International Journal of Quality & Reliability Management*, 36(1), 25–39. [CrossRef]
- Fatima, T., & Elbanna, S. (2020). Balanced scorecard in the hospitality and tourism industry: Past, present and future. *International Journal of Hospitality Management*, 91, 102656. [CrossRef] [PubMed]
- Gallo, P., Timková, V., Šenková, A., & Karahuta, M. (2018). Use of dashboards in predicting the development of the company using neural networks in hotel management. *Geojournal of Tourism and Geosites*, 22(2), 307–316.
- Gour, A., Aggarwal, S., & Erdem, M. (2021). Reading between the Lines: Analyzing online reviews by using a multi-method web-analytics approach. *International Journal of Contemporary Hospitality Management*, 33(2), 490–512. [CrossRef]
- Grandhi, B., Patwa, N., & Saleem, K. (2021). Data-driven marketing for growth and profitability. *EuroMed Journal of Business*, 16(4), 381–398. [CrossRef]
- Gultom, R. A., Mustofa, F. J., & Tanaga, S. M. (2026). The role of artificial intelligence based decision support systems in managerial decision-making in the hospitality industry: A systematic literature review. *Community Engagement & Emergence Journal*, 7(3), 2138–2155. [CrossRef]
- Han, X. (2025). Value chain-oriented cost control in tourist hotels: A data-driven performance evaluation using DEA and AHP. *International Journal of Information Systems in the Service Sector*, 16(1), 1–15. [CrossRef]
- Heo, C. Y., & Schegg, R. (2026). Structural resources or managerial cognition? Explaining hoteliers' perceived impact of artificial intelligence in hospitality. *International Journal of Hospitality Management*, 139, 104788. [CrossRef]
- Ibrahim, N., & Handayani, P. W. (2022). A systematic literature review of business intelligence framework for tourism organizations: Functions and issues. *Interdisciplinary Journal of Information, Knowledge, and Management*, 17, 523–541. [CrossRef] [PubMed]
- Kahlke, R., Poth, C., Young, J. S., & Maggio, L. A. (2026). State of the methods for integrating qualitatively oriented critical review approaches with bibliometrics: A mixed critical bibliometric approach. *International Journal of Qualitative Methods*, 25, 1–15. [CrossRef]
- Kaviya, D., & Meera, C. (2026). AI-driven financial forecasting for the hospitality industry: Optimising revenue and operational decisions through predictive analytics. *International Journal of Emerging Technologies and Innovative Research*, 13(4), b754–b763. [CrossRef]
- Khaghaany, M., Kbelah, S., & Almagtome, A. (2019). Value relevance of sustainability reporting under an accounting information system: Evidence from the tourism industry. *African Journal of Hospitality, Tourism and Leisure*, 8, 1–12.
- Klarin, A. (2024). How to conduct a bibliometric content analysis: Guidelines and contributions of content co-occurrence or co-word literature reviews. *International Journal of Consumer Studies*, 48(2), e13031. [CrossRef]
- Kocourek, M., Chalupa, Š., & Petricek, M. (2025). Deconstructing revenue management decision-making: Analyzing the influence of individual factors in small and medium-sized hospitality enterprises. *TEM Journal*, 14(3), 2090–2097. [CrossRef]
- Mariani, M., Baggio, R., Fuchs, M., & Höepken, W. (2018). Business intelligence and big data in hospitality and tourism: A systematic literature review. *International Journal of Contemporary Hospitality Management*, 30(12), 3514–3554. [CrossRef]
- Mohammed, I., & Denizci Guillet, B. (2025). Stakeholder perspectives on integrating explainable artificial intelligence into hotel revenue management system. *Tourism Economics*, 32(4), 804–824. [CrossRef]
- Nicolau, J. L., Xiang, Z., & Wang, D. (2024). Daily online review sentiment and hotel performance. *International Journal of Contemporary Hospitality Management*, 36(3), 790–811. [CrossRef]
- Nikić, L., & Laškarin Ažić, M. (2025). Artificial intelligence and emerging tools for pricing optimization in hotel revenue management: Systematic literature review. In *Proceedings of the international conference on new ideas in management, economics & accounting*. dPublication. Available online: <https://www.dpublication.com/wp-content/uploads/2025/11/D0Pe8gu8wPnZvf11C65H.pdf> (accessed on 30 July 2026).

- Nunes, C. R., & Machado, M. J. C. V. (2012). O balanced scorecard na hotelaria e turismo. *Tourism & Management Studies*, 2, 722–733. Available online: <https://tmstudies.net/index.php/ectms/article/view/238> (accessed on 20 September 2026).
- Pavone, P., Migliaccio, G., & Simonetti, B. (2023). Investigating financial statements in hospitality: A quantitative approach. *Quality & Quantity: International Journal of Methodology*, 57(3), 383–407. [\[CrossRef\]](#)
- Pereira, L. N., & Cerqueira, V. (2022). Forecasting hotel demand for revenue management using machine learning regression methods. *Current Issues in Tourism*, 25(17), 2733–2750. [\[CrossRef\]](#)
- Quesado, P., & Miranda, H. (2026). The balanced scorecard as a communication, alignment, and strategic information system in a local accommodation company. *International Journal of Marketing, Communication and New Media*, 25–41. [\[CrossRef\]](#)
- Ribarić Čučković, E. (2020). Quality cost accounting in the hospitality industry. *Tourism and Hospitality Management*, 26(1), 249–252.
- Ryoo, G., Shin, S. W., & Ko, Y. D. (2026). KPI-based management dashboard for hotel industry: A case study of Eland Park. In *Proceedings of the 7th Asia Pacific conference on industrial engineering and operations management* (pp. 1664–1665). IEOM Society International. [\[CrossRef\]](#)
- Saitta, S., D’Amico, V., & Farinella, G. (2024). Dynamic price prediction for revenue management system in hospitality sector. In *Proceedings of the 13th International Conference on Data Science, Technology and Applications—DATA* (pp. 218–228). SciTePress. [\[CrossRef\]](#)
- Saitta, S., D’Amico, V., & Farinella, G. M. (2026). Predictions of hotel dynamic pricing for revenue management system. In A. Cuzzocrea, S. Hammoudi, E. Benkhelifa, & O. Gusikhin (Eds.), *Data management technologies and applications. DATA 2024. Communications in computer and information science* (Vol. 2883). Springer. [\[CrossRef\]](#)
- Saleh, M. M. A., Jawabreh, O. A. A., Al Om, R., & Shniekat, N. (2021). Artificial Intelligence (AI) and the impact of enhancing the consistency and interpretation of financial statement in the classified hotels in Aqaba, Jordan. *Academy of Strategic Management Journal*, 20(3), 1–18.
- Szrajber, B. E., & Alon, I. (2026). Reconciling qualitative and quantitative approaches within bibliometrics. *Multinational Business Review*, 34(2), 303–322. [\[CrossRef\]](#)
- Tajeddini, O., Tajeddini, K., Gamage, T. C., & Hameed, W. U. (2026). Smart insights, stronger performance: Leveraging business intelligence and dynamic capabilities in tourism and hospitality. *International Journal of Hospitality Management*, 133, 104410. [\[CrossRef\]](#)
- Visentin, M., Reis, R. S., Cappiello, G., & Casoli, D. (2021). Sensing the virus: How social capital enhances hoteliers’ ability to cope with COVID-19. *International Journal of Hospitality Management*, 94, 102820. [\[CrossRef\]](#) [\[PubMed\]](#)
- Xie, K. L., & So, K. K. F. (2018). The effects of reviewer expertise on future reputation, popularity, and financial performance of hotels: Insights from data-analytics. *Journal of Hospitality and Tourism Research*, 42(8), 1187–1209. [\[CrossRef\]](#)
- Yandamuri, U. S. (2024). AI-driven decision support systems for operational optimization in hospitality technology. *Metallurgical and Materials Engineering*, 30(4), 950–958.
- Zayed, L. M. M., Nour, M. I., Al Attar, K., Almubaideen, H., & Abdelaziz, G. A. M. (2024). Role of Artificial Intelligence (AI) in accounting information systems in detecting fraud. *Studies in Systems, Decision and Control*, 528, 397–409. [\[CrossRef\]](#)

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