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# Applications of machine intelligence and decision analytics in hospitality: a systematic review

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**ABSTRACT**

This systematic review synthesizes how machine intelligence (MI) and decision analytics (DA) are deployed across hospitality functions (customer relationship management (CRM)/personalization, revenue management (RM) and pricing, and operations) and clarifies barriers and research frontiers. Following a PRISMA-oriented protocol for the 2008–2025 period, the study searched Scopus, Web of Science, IEEE/Elsevier, and SpringerLink using combined terms for MI/artificial intelligence (AI)/machine learning (ML) and hospitality/tourism with CRM, revenue/pricing, forecasting, and operations. The inclusion criteria focused on peer-reviewed English studies reporting concrete models/applications or empirical evidence. Studies were thematically coded into four streams: CRM and personalization; RM and dynamic pricing; operations and scheduling; and governance (privacy/ethics/skills). The findings consistently show that MI/DA improves customer segmentation, demand forecasting, dynamic pricing (revenue per available room (RevPAR)), and workforce/maintenance efficiency. Yet, adoption is slowed by data governance (privacy/general data protection regulation (GDPR)) and siloed systems. Unlike prior broad IT/e-Tourism reviews, this study integrates recent MI advances (spatiotemporal deep learning, real-time decisioning, and human–AI teaming) into a hospitality-specific decision pipeline and outlines a testable research agenda around scalability/drift, privacy-by-design, and controlled field experiments.



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## 1. INTRODUCTION

The hospitality sector is increasingly shaped by changing customer expectations, intense competition, rapid technological development, and the need for higher operational efficiency. Hotels, restaurants, travel services, and tourism-related businesses now rely heavily on data to understand customers, enhance service quality, forecast demand, manage prices, and support strategic decision-making. Within this context, machine intelligence (MI) and decision analytics (DA) have become essential tools for improving performance and strengthening competitiveness in the hospitality industry [1].

In this study, MI refers to computational approaches that enable systems to recognize patterns, learn from data, and support automated or semi-automated decisions. These approaches include artificial intelligence (AI), machine learning (ML), deep learning, natural language processing, reinforcement learning, fuzzy logic, expert systems, intelligent agents, robotics, computer vision, augmented reality, and virtual reality [1]. DA refers to the use of descriptive, predictive, and prescriptive methods to transform data into

useful managerial decisions. It includes forecasting, optimization, simulation, clustering, feature selection, multi-criteria decision-making, and other analytical techniques that support business planning and problem-solving. MI and DA help hospitality firms move beyond traditional reporting toward faster, evidence-based, and more personalized decision-making [2], [3]. Hospitality is a broad and dynamic industry that includes lodging, food and beverage services, travel, tourism, transportation, attractions, entertainment, and related customer experiences [4]. The sector contributes significantly to economic activity and employment, while many destinations depend on it as a major source of income. At the same time, hospitality organizations compete mainly through customer experience. Guests increasingly expect fast service, personalized offers, reliable information, flexible booking options, and consistent value. Therefore, hospitality firms must continuously improve how they collect information, understand customers, and respond to market changes [5].

MI and DA can support several core hospitalities functions. In customer relationship management (CRM), they help analyze guest preferences, personalize offers, predict satisfaction, segment customers, and improve loyalty programs. In revenue management (RM), they support demand forecasting, dynamic pricing, room allocation, and promotional decisions. In operations, they assist workforce scheduling, fraud detection, service automation, inventory control, and resource optimization. Tools such as chatbots, recommendation systems, sentiment analysis, robotic services, and predictive dashboards are increasingly used to improve customer experience and managerial efficiency [6]. This review examines MI and DA applications in hospitality from 2008–2025, focusing on CRM and personalization, RM and pricing, and operational decision-making. It also considers governance, privacy, ethics, workforce readiness, and data quality. Overall, the study argues that MI and DA should be viewed not only as technological tools but as part of a broader decision-making ecosystem connecting data, people, processes, and strategy.

## 2. BACKGROUND THE STUDY

Today's business environment is increasingly shaped by data, rapid technological innovation, and rising customer expectations. Within this context, the hospitality sector has become deeply involved in digital transformation, using advanced technologies to improve operational efficiency, enhance customer engagement, and support strategic decision-making [7]. One of the most important developments in this transformation is MI, which enables organizations to use data and computational tools to generate customer insights and identify practical business improvements. Alongside MI, DA is increasingly being applied across key hospitality functions, particularly CRM, personalized marketing, and RM [8]. CRM represents one of the most significant areas in which MI and DA can create value for hospitality organizations. Many hotels and tourism-related businesses already use CRM systems to collect, organize, and manage customer data throughout the customer life cycle. However, when CRM is supported by advanced analytics, hospitality firms can move beyond broad and generic campaigns toward more accurate segmentation and targeted communication. Rather than using a one-size-fits-all marketing approach, firms can analyze customer behavior, preferences, purchase history, booking patterns, and feedback to design more relevant services and messages. This enables organizations to understand customers more deeply and build stronger relationships through data-driven personalization [9]. Personalized marketing is another major application of MI in hospitality. Without intelligent analytics, customers often receive standardized offers that may not correspond to their actual needs or travel preferences. MI-supported tools can classify customers into refined segments and identify subtle differences in their behavior. Techniques such as market-basket analysis can recommend relevant products and services, including hotels, flights, restaurants, and travel packages, based on previous behavior and expected preferences. Such personalization can enhance customer satisfaction, increase engagement, and strengthen brand loyalty. Since customer experience is a central source of competitive advantage in hospitality, personalized marketing helps firms provide offers that are more timely, relevant, and persuasive [9].

RM has also been substantially affected by MI and DA. Since the 1990s, hospitality firms have increasingly adopted automated RM systems that combine data management and predictive analytics to forecast demand and optimize pricing [10]. Predictive analytics helps organizations understand customer behavior, anticipate booking patterns, and determine how to sell limited resources such as rooms, restaurant capacity, and travel services across multiple distribution channels. Through dynamic pricing and demand forecasting, firms can adjust prices according to market conditions, customer demand, competitor behavior, and seasonal fluctuations. These analytics-based decisions improve revenue performance and support more efficient use of fixed resources [10]. The integration of MI and DA into operational practices and decision-support systems has generated important benefits for hospitality stakeholders. MI can support professional, administrative, and structural processes by enabling faster and deeper analysis, improving policy knowledge, reducing duplication, saving resources, and accelerating the application of findings in practice [11].

These advantages are especially relevant in a sector characterized by intense competition, unstable demand, and high customer expectations.

Nevertheless, MI and DA cannot independently guarantee improved performance. Their value depends on their integration with human intelligence, managerial judgment, and business insight. Strategic transformation therefore requires not only the redesign of marketing strategies but also the reconfiguration of work processes and organizational capabilities [12]. Firms that successfully integrate MI into their strategies may develop a competitive advantage, whereas those that fail to do so may face increasing disadvantages [13]. The relationship between hospitality firms and their guests remains central to service success. Hotels, cruise companies, restaurants, airlines, and other service providers depend on repeat visits, customer loyalty, and positive experiences. The emergence of the industrial internet of things (IIoT) and data analytics has changed how hospitality organizations interact with potential and existing customers. Large amounts of data are generated when customers visit websites, compare prices, search for amenities, read reviews, make bookings, cancel reservations, or provide feedback. These data points reveal behavioral patterns that hotels and travel companies can use to tailor services to individual guests. In hotel operations, CRM involves collecting and interpreting customer data to manage business relationships, establish referral networks, and retain profitable customers.

Three CRM elements are particularly relevant to hospitality: acquisition, cultivation, and reinforcement [14]. Acquisition refers to collecting data from different sources, including check-in records, contact details, passport information, booking platforms, and digital interactions. Cultivation involves analyzing accumulated data to understand customer purchasing patterns and service preferences over time. Reinforcement refers to gathering feedback and using it to improve or modify services. Through these stages, CRM becomes more than a database; it becomes a strategic system for understanding customers and improving service relationships [14]. Bibliometric evidence also indicates growing scholarly interest in MI and AI applications in tourism and hospitality. Based on Scopus-exported records related to MI in hospitality and tourism, much of the research appears in computer science and technology-oriented journals and conference proceedings [15]. This pattern suggests that AI-related hospitality research is increasingly shaped by the intersection of tourism studies, information systems, computer science, and data analytics. In the hospitality sector, MI adoption in RM has been particularly important, although its application has sometimes remained limited to system design and development. Revenue managers use predictive analytics to forecast demand, identify customer segments, analyze booking patterns, and monitor market trends [16]. RM systems, including dynamic pricing systems, are often integrated into property management systems to optimize prices for rooms, spa services, dining, and other hotel experiences. Revenue managers may combine customer purchasing behavior, demand patterns, and competitor offerings to develop pricing strategies that increase yield and maximize total revenue. In this way, data analytics enables a more comprehensive pricing approach that links revenue objectives with customer-centered experiences [17].

The development of central reservation systems, website booking engines, and distributed platforms has increased the potential for real-time analysis and price adjustment [18]. These systems allow hotels to observe demand patterns quickly and adjust prices across different channels. RM systems may use market trends, enterprise resource planning data, predictive analytics, reactive analytics, and pricing optimizers to manage selling prices and sales costs. They may also store demand data based on customer responses to earlier pricing decisions, including periods when competitors performed better or worse. This information supports planning and helps firms balance competitive pricing with customer price perception. Dynamic pricing is particularly valuable in markets where data remain valid for only short periods. Because demand conditions change continuously, pricing decisions must be updated using real-time information. Effective RM systems therefore require large-scale price management, rapid price delivery, reliable data quality, and integration across distribution channels. However, technology does not automatically create competitive advantage. Its effectiveness depends on whether managers understand its limitations and incorporate it appropriately into decision-making. When properly implemented, RM systems help hospitality firms coordinate price adjustments across booking channels and sell negotiated rates according to demand.

Figure 1 shows distribution of AI/MI-related publications in tourism and hospitality by publication outlet, 2008–2025. The results show that Lecture Notes in Computer Science including subseries is the most prolific source in terms of the number of publications, followed by Lecture Notes of the Institute for Computer Sciences and Internet Research. This suggests that most of the research on AI and MI in tourism and hospitality has been published in interdisciplinary and technology focused outlets rather than solely in hospitality journals. Many publications in journals such as Sensors, Smart Innovation Systems and Technologies, and Information Systems Frontiers also show the relationship between AI applications, data systems, smart technologies, and service innovation. In general, the figure shows a growing academic interest in the application of intelligent

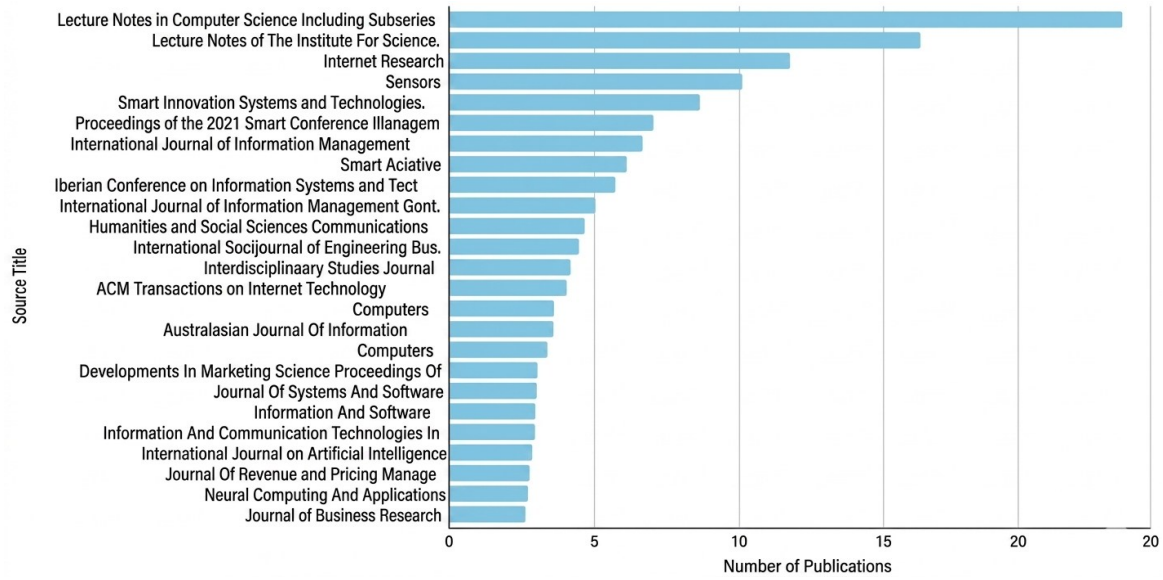


Figure 1. Distribution of AI/MI publications in tourism/hospitality by outlet (2008–2025)

## 3. METHOD

### 3.1. Data privacy and security concerns

The provision of MI-based services and products in hospitality necessitates the collection of substantial amounts of customer data. On one hand, the sector is already quite heavily regulated with respect to the protection of customer data, especially when comparing the U.S. and Europe, where data protection laws significantly dictate control aspects both at home and abroad. International companies are typically required to comply with the statutory privacy regime in each European country where they operate. Of particularly significant material relevance, especially for luxury hotels, is the general data protection regulation (GDPR), which has been introduced in the European Union and is applicable extraterritorially, i.e., worldwide. Additionally, the public is becoming increasingly aware of data breaches, and consequently of the potential for unauthorized access to their personally identifiable information, which might lead to identity theft. The subsequent high degree of uncertainty about, and lack of control over, who might access their data, combined with consumers' generally low level of technical knowledge, means that customers often view data as a characteristic of trifling importance. For such reasons, user consent, as legally outlined in the GDPR, is an essential point vis-vis the use of customer and personnel data in the supply of technology-based services and products [19]. The largest prerequisite to utilizing the insights provided by technology is the ability of human capital to 'transcend' technology in using it to create or improve products and services on offer. This means that hospitality establishments may need to channel resources into staff training for effective utilization of tools to occur. Additionally, increasing staff proficiency in decision-making or data management will also cultivate a smart-working culture that promotes the appropriate integration of advanced analytics technologies. Several staff, however, may resist the adoption of these technologies because they do not feel comfortable that their job security in the industry will grow as these technologies develop. Therefore, it is important for professionals in the hospitality industry to understand and resolve issues surrounding worker attitudes to technological development.

Staff training and development refer to strategies entailing continuous training and support for staff members to mold their skills, knowledge, and attitudes where technology is concerned. Staff training tends to lead to the best organizational results when training strategies focus on generating staff 'proactive dispositions' to technology such as interest, enjoyment, and a willingness to learn as opposed to merely how to use a piece of technology. This is important as, in the absence of this, staff will struggle to utilize the technology efficiently and find innovative ways to make the technology work for their role. Leadership plays an important role in enhancing the attitudes of staff members towards tech application. Training, however, will aid in renewing the attitudes towards leadership by portraying how technology influences outcomes. Efforts to enhance technology proficiency in hospitality settings have been proven to enhance a hotel's reputation and performance, and hotels that have a better digital skill mix have a pricing strategy that leads to better profits.

### 3.2. Search strategy and selection criteria

This study defined explicit inclusion and exclusion criteria a prior to ensure transparent and reproducible study selection as shown in Table 1. Database search strings and filters: searches were executed on February 16, 2026. Where supported, queries were applied to titles, abstracts, and author keywords, and limited to English-language records within 2008–2025. The exact strings used are provided in Table 1.

Table 1. Exact database search strings (executed 16 February 2026)

| Database | Search string (as executed) | Filters/fields |
|---|---|---|
| Scopus | TITLE-ABS-KEY(("machine intelligence" OR "artificial intelligence" OR "machine learning" OR "deep learning" OR "neural network*" OR "data mining" OR "predictive analytics") AND (hospitality OR hotel* OR tourism OR travel OR restaurant* OR "food and beverage" OR airline* OR cruise* OR "guest experience") AND (CRM OR "customer relationship management" OR personaliz* OR recommend* OR "sentiment analysis" OR forecast* OR "demand forecasting" OR "revenue management" OR pricing OR "dynamic pricing" OR optimization OR schedul* OR "decision support" OR "decision analytics")) | PUBYEAR 2008–2025; English; document types: article, conference paper, book chapter |
| Web of Science Core Collection | TS=(("machine intelligence" OR "artificial intelligence" OR "machine learning" OR "deep learning" OR "neural network*" OR "predictive analytics") AND (hospitality OR hotel* OR tourism OR travel OR restaurant* OR "food and beverage") AND (CRM OR "customer relationship management" OR personaliz* OR recommend* OR forecast* OR "revenue management" OR pricing OR optimization OR schedul* OR "decision support" OR "decision analytics")) | Timespan 2008–2025; English; document types: article, proceedings paper, book chapter |
| IEEE Xplore | ("All Metadata":"machine learning" OR "All Metadata":"artificial intelligence" OR "All Metadata":"decision support" OR "All Metadata":"optimization") AND ("All Metadata":hospitality OR "All Metadata":hotel OR "All Metadata":tourism) | Years 2008–2025; English; metadata fields; peer-reviewed conference/journal content |
| SpringerLink/ ScienceDirect | ("machine learning" OR "artificial intelligence" OR "decision analytics" OR "predictive analytics") AND (hospitality OR hotel OR tourism) AND (CRM OR personalization OR recommendation OR forecasting OR "revenue management" OR pricing OR optimization) | Years 2008–2025; English; full text search; peer-reviewed content |

### 3.3. Study selection, reviewers, and disagreement resolution

Titles/abstracts and full texts were screened independently by two reviewers. Disagreements were resolved through discussion; if consensus was not reached, a third senior reviewer adjudicated. Screening decisions and reasons for exclusion were logged to improve transparency and reproducibility.

### 3.4. Quantitative synthesis (bibliometric overlay)

Along with qualitative thematic synthesis, quantitative descriptors of the evidence base is reported. The final reference list was used to produce bibliometric summaries (e.g., studies/year and by study type) and to create visual trend plots. Keyword co-occurrence: keyword co-occurrence was analyzed using the co-word approach. The same analysis can be executed in VOSviewer or Biblioshiny using the finalized dataset exported from Scopus/Web of Science.

Table 2 operationalizes the review protocol, describing transparent eligibility criteria (inclusion/exclusion), and the quality screen that resulted in the final evidence base before quantitative description and thematic synthesis. The criteria are designed to balance coverage and rigor. First, the restriction of the publication window to 2008–2025 places the analysis in the context of the current diffusion of MI and DA in hospitality, reducing historical noise while maintaining sufficient longitudinal variation to compute trend descriptors (e.g., studies/year). Second, limiting the document types to peer-reviewed journal articles, conference proceedings, and scholarly book chapters improves reproducibility and methodological traceability, while excluding editorials, practitioner pieces, theses, and abstracts-only records reduces the risk of non-verifiable claims and incomplete reporting.

The topical scope criterion provides a mechanism to ensure industry relevance through the requirement of hospitality/tourism settings with operational or managerial implications, thus preventing dilution from adjacent domains where context transferability is uncertain. The conceptual fit rule adds to construct validity by rejecting papers that mention AI/analytics without a specified method, application, and evaluative component—an important guardrail in an area of rapid growth where "AI" may be used rhetorically rather than analytically. Finally, the quality filter depends on outlet credibility (Scopus/Web of Science indexed or reputable publishers), full-text availability, de-duplication, and minimal methodological transparency (data source, technique, evaluation, and outcomes). These rules offer a defensible basis for the review's quantitative descriptors (bibliometric summaries and trend plots) and for replicable co-word keyword analysis in VOSviewer/Biblioshiny with the finalized dataset. Hence, the table is a methodological "audit trail" for validity, comparability and replicability of the review's findings.

Table 2. Study selection and quantitative descriptors (2008–2025)

| Criterion | Inclusion | Exclusion | Quality/notes |
|---|---|---|---|
| Publication year range | 2008-2025 (inclusive). | Before 2008 or after 2025. | Captures the modern era of MI/DA adoption and evidence relevant to current practice. |
| Document type | Peer-reviewed journal articles; peer-reviewed conference proceedings; peer-reviewed book chapters (e.g., Springer/Elsevier) reporting original empirical results or validated models. | Editorials/commentaries, news items, trade/practitioner articles, theses/dissertations, working papers, non-peer-reviewed preprints, and abstracts-only records. | Peer-review status and reportability of methods/results were required for extraction. |
| Language | English-language publications. | Non-English publications. | Aligned with the review team's screening capacity and consistency of coding. |
| Topical scope | Hospitality and tourism contexts (e.g., hotels/lodging, F&B, airlines/cruises, and attractions) with explicit operational/managerial relevance. | Studies focused on non-hospitality domains without a transferable hospitality context. | Prevents dilution of findings with unrelated industry evidence. |
| Conceptual fit | Studies that apply or evaluate MI/AI/ML and/or DA techniques (e.g., prediction, optimization, recommendation, NLP, and reinforcement learning) with a describable method and outcome/implication. | Studies that merely mention AI/analytics without a method, application, or evaluative component; purely descriptive or generic IT adoption pieces. | Minimum methodological transparency required (problem definition, technique, and reported outputs). |
| Quality filter | Published in peer-reviewed outlets indexed in Scopus and/or Web of Science or hosted by established scholarly publishers (IEEE, Elsevier, and SpringerLink); full text accessible; duplicates removed; sufficient methodological detail for extraction. | Predatory or unverifiable outlets; duplicate records; inaccessible full texts; insufficient information to extract key variables (data source, method, evaluation, or outcomes). | Indexing/publisher checks plus a transparency screen during full-text assessment. |

### 3.5. Case studies and success stories

This section presents a number of case studies and success stories from the field, where MI, DA, and human capability are explored in more detail. These examples highlight how theory, data, and knowledge can inform practice in the real world. The organizations are in different hospitality settings such as a casino, five-star hotel, resort hotel complex, franchise-based restaurant, and attraction [20]. Together, the collection of cases and success stories represents the pervasive force of MI, DA, and human capability, and each demonstrates the many organizational and competitive opportunities such systems present today.

In each case example, these various applications of analytics have demonstrated promising results, including better marketing strategies for personalized service, better predictions, and thus better strategic planning of staffing and, to some extent, better control over energy consumption and energy costs. There are several management implications, which are also retrieved from both the consumer survey and the industry representative study [21]. The industry representatives experienced real progress from adopting MI and DA. One was the significant role played by the technology provider in terms of establishing and maintaining a relationship with the hospitality business. Lessons learned and best practices derived from the case examples suggest that firms benefiting from using MI and DA technology are those that can absorb knowledge from technology providers and attract predictive analytic talent to their firm. The provision of MI-based services and products in hospitality necessitates the collection of substantial amounts of customer data.

With the abundance of data that can support decision making, operations across hospitality enterprises can be optimized, reducing costs, improving service speed, and enhancing customer satisfaction. These developments have accelerated the use of DA in hospitality operations. Accordingly, this section reviews empirical and conceptual studies that apply DA, including the types of data used, how data are collected and curated, and the analytical models employed—from descriptive approaches to predictive and prescriptive models.

Pricing is an important tactic for hoteliers to increase revenue and offer more tailored products to different consumer segments. Traditional hotel pricing theories use demand for short-term forecasting to determine the optimal price point. With the use of conventional pricing, where forecasts are revised 7–30 days before arrival, hoteliers use time-controlled pricing methods to modify prices in response to the level of demand [22]. For example, more expensive premium rates during the high-demand season, with price decreases to stimulate demand during the low season. The traditional static pricing method no longer meets the demands of the current environment. With the optimal price being calculated at the time of the customer's arrival, hotels can use DA to change prices dynamically. Thus, information on factors affecting

demand can be used to dynamically adjust prices in real time based on customer-product interaction, enabling each sales unit to maximize revenue optimization.

Another research interest is the allocation of services and resources required by the customer based on the specific value of the customer in question. Using spreadsheets for DA, customer value using the customer lifetime value can be used indefinitely. Other topics of interest are service process management, service efficiency management, customer retention management, hotel service quality management, and social media. Decision-making applications in the field of hospitality operations have demonstrated various aspects of improving operational practices in the hospitality industry. However, deciding whether to employ this method in the real world is a different story, as the survey also reveals a variety of reasons why hotels do not utilize the method. First, the opening question reveals that hotel staff are interested in utilizing data analytics, but few are eager to make it their principal approach to better comprehend and meet their customers' needs.

Pricing becomes complicated due to the interaction between different market segments, price sensitivity, and some service characteristics that may not be homogenously priced [23]–[28]. A price point and price structure can, however, be identified by analyzing an establishment's demand curve and cost structure. Furthermore, additional benefits can be derived from continuously analyzing consumer demand whenever short-term and dynamic price changes are not expected. It is important to point out that dynamic pricing models usually simultaneously maximize revenue while lowering customers' resistance. A transparent pricing strategy is appreciated by customers and adds value to the product. For example, some cruise liners have been very successful in this area by using a campaign that emphasizes

The allocation and management of resources is critical for the efficient operation of any hospitality entity. Many operational functions of the hospitality sector rely on the deployment of sufficient complementary resources. For example, patrolling and inventory staff, kitchen staff, service staff, and data analytics can play a significant role in making the most of those resources while assisting operation management in decision-making.

One of the key concepts necessary for operational functions is the need for the deployment of data analytics, which can be operational through the allocation of resources involved in the operational workflow. As the workflow is highly dependent on real-time demands of customers, firms in industries such as service and hospitality need real-time data to better manage resources, hence increasing service efficiency. Empirical studies have shown that this approach is beneficial, especially in hotels, given that hospitality is labor-intensive and has the potential to increase the efficiency of operation management functions. Another application of analytics in operational functions can be found in exploring how complementary resources could be optimally distributed across different operational job functions to maximize performance.

Empirical evidence finds that data analytics in this form is beneficial, as significant enhancements in performance can be achieved by maximizing the allocation of available resources [29]. The time series data collected over user lifespans can be fed into predictive algorithms to accurately forecast user participation in the future. Predictive analytics can be further applied to forecast job functions or services required at different times across operational executions. The advantage of using predictive analytics is its reliance on historical user activity data, hence the computation of the observed sample can be bias-free. Predictive analytics, therefore, tend to reduce costs while simultaneously increasing the accuracy of forecasts. Introducing data analytics in the operations function of any industry is not without challenges. First and foremost, the existing setups must be adjusted to accommodate data analytics. Most existing operations are not designed and vetted for the application of analytics [30]–[32]. Many systems are manually driven; hence, staff may not trust any analytics and may seek to sabotage the projected benefits. More importantly, both touching and nontouchable employees need to be made aware that changing the operational course to accommodate analytics will not change their jobs, as operations will still be performed by humans; analytics is just a tool like any other tool. It is, therefore, necessary to ensure that employees are data literate and in touch with the data revolution currently changing the nature of operations and decision-making in most service industries.

## 4. RESULTS AND DISCUSSION

While reviewing the previous section and exploring various advancements and capabilities of ML, AI, big data, and robotics in the current context, we can investigate a string of studies focusing on the implementation of these technological advancements in the hospitality sector [33]. This section critically examines the literature and offers in-depth evidence on the challenges and barriers existing in the implementation of MI (including AI/ML) and DA; and discusses the various factors contributing to this. Data privacy and security are the two main components that are equally divided into six research studies. It is unanimously accepted by the researchers that guests do not want their data gathered, so policies against

sharing guest data have resulted in the adoption of multiple systems, redundancies in data gathering, and siloed storage for each property, leading to the unavailability of a 360-degree view of the customer.

### 4.1. Quantitative synthesis: bibliometric and trend overview

To complement the narrative synthesis, we provide a compact quantitative overview of the reviewed evidence base. Figure 2 shows publication trends by year (derived from the reference list used in this review; N =45). Figure 3 summarizes the relative prevalence of ML/AI and DA techniques mentioned across the review text (proxy indicator). Figure 4 illustrates the frequency of MI/AI and DA techniques mentioned in the studies included in this review. This figure provides a proxy indicator of the relative prominence of each technique within the reviewed studies.

Figure 2 illustrates the annual publication trend of the studies included in this review, using only the reference list retained after the screening and eligibility stages. The trend shows a low research volume in the early years, with a clear increase in recent years. The upward trend indicates that MI and DA in hospitality have transitioned from a niche interest to a primary research stream, likely fueled by the availability of more data, advancements in computing, and the growing operational need for automation and personalization. This growth also reflects increasing management attention on applications such as CRM, recommendation and personalization, demand forecasting, dynamic pricing and revenue optimization. Importantly, the figure does not only show "more papers," but also a broadening of methodological experimentation, from early rule-based or descriptive approaches to more data-driven models (e.g., supervised learning, ensemble methods, and hybrid analytics). Overall, the publication trend supports the argument of the review that the field is rapidly evolving with newer studies increasingly addressing real-time decision support and scalable deployment issues. However, the number should be read as a tendency within the corpus selected, i.e. it depends on the criteria of inclusion of a review and on the coverage of the database, and not on the totality of the universe of research in hospitality.

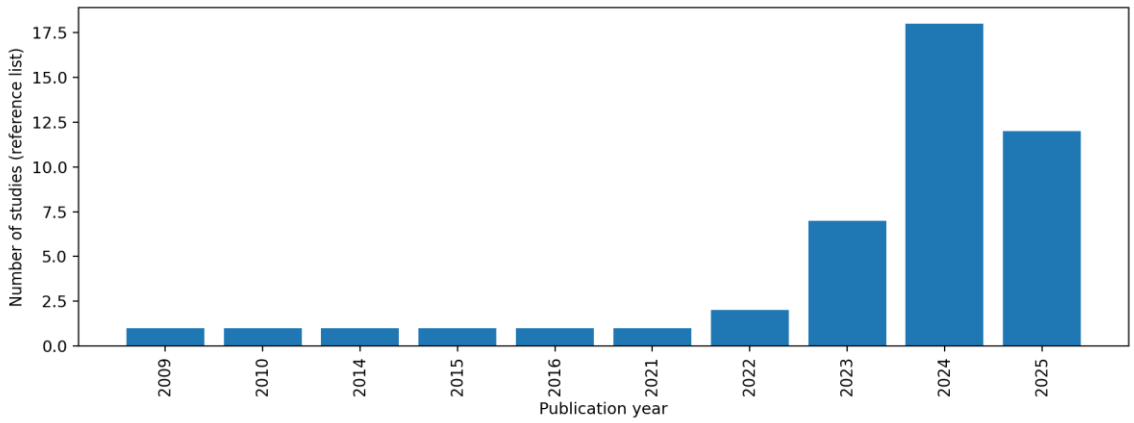


Figure 2. Annual publication trend of included studies by publication year (2008–2025)

Figure 3 summarizes the relative frequency of specific ML, AI, and DA techniques mentioned in the studies discussed in this review. Note that the figure is a proxy indicator. It reports the frequency of methods found in the reviewed text and synthesis, not an exact count of how many studies employed each technique as their primary model. Even with this caveat, the distribution is informative in that it indicates which approaches dominate the field's discourse and practice. In general, the figure shows a concentration around a small number of widely used techniques. The most commonly used approaches are traditional predictive models and the "workhorse" ML algorithms (e.g. artificial neural networks (ANN), support vector machines (SVM), random forest (RF), and other tree-based or ensemble methods). This suggests that hospitality applications tend to favor methods that strike a balance between performance, implementability and interpretability. The appearance of optimization and DA tools (e.g., linear/nonlinear programming, simulation, heuristic optimization, and multi-criteria decision-making (MCDM)) indicates that the literature is not purely predictive, but also addresses operational decisions such as pricing, RM, capacity allocation, and service design. Thus, Figure 3 provides a high-level map of methodological emphasis in the reviewed corpus, in order to identify dominant toolkits, under-explored methods, and opportunities for future research to move beyond often repeated algorithms to stronger validation, transparency, and real-world deployment.

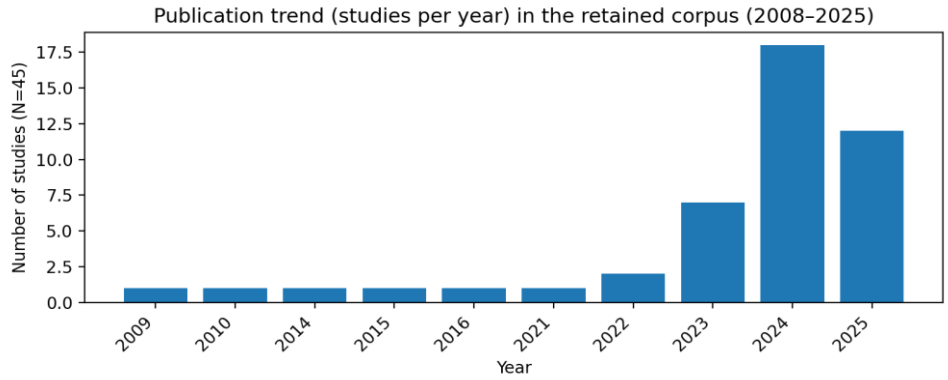


Figure 3. Publication trend (studies per year) according to the reference list that was used in this review

The research that is shown in the chart talks about MI/AI and DA methodologies as in Figure 4. Most of the literature is on recommendation/personalization and dynamic pricing/RM. This indicates that the most discussed application areas are personalization and price choices affecting customers. Forecasting is quite popular too which means people are still interested in predicting demand. Optimization is discussed at a reasonable level, but more sophisticated approaches such as deep learning and reinforcement learning are less discussed. There are not many traditional models (ANNs, SVM, RF, and decision trees) and decision tools (MCDM, programming, and simulation). Frequencies are counts from the synthesized text that stand in for emphasis, not actual technique use.

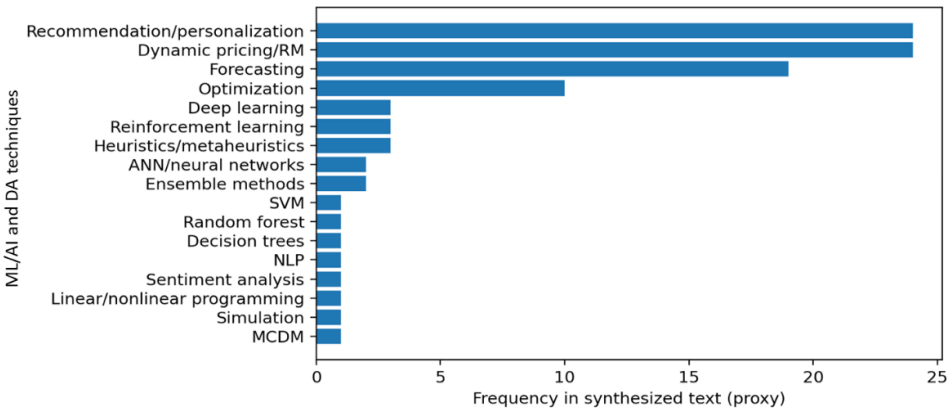


Figure 4. Frequency of MI/AI and DA techniques mentioned in included studies (proxy indicator)

Figure 5 visualizes a keyword co-occurrence network that shows the intellectual relationship between the core concepts of the reviewed literature. Co-word links are calculated at the paragraph level, i.e. two keywords are linked if they co-appear in the same paragraph of the review text synthesized. Hence, robust or dense links reflect themes that are usually covered in close conceptual proximity, while weaker links capture more niche or emerging topics. In this way the network acts as a "map" of the field, not only showing what keywords are common but also how they cluster into meaningful research conversations.

In general, the network is supposed to produce several thematic clusters. One cluster tends to be about intelligence that faces customers, with terms like CRM, customer satisfaction, personalization, recommendation, sentiment analysis and social media analytics co-occurring, which indicates research that applies ML/AI to improve experience and engagement. A second cluster is often about revenue and operations DA, with keywords such as RM, demand forecasting, dynamic pricing, occupancy, optimization, and scheduling—with a focus on studies that convert predictive outputs into actionable managerial decisions. A third, often smaller, cluster may relate to data and governance including big data, IoT, privacy, transparency, and explainability, showing increased concern with implementation constraints and responsible use.

The co-word network can be reproduced using tools such as VOSviewer or Biblioshiny, for which methodological transparency is also ensured: researchers can recreate the map from the final dataset and experiment with the extent to which results change with different thresholds or keyword cleaning rules. Overall, Figure 4 supports the review synthesis by identifying the dominant thematic structure of MI and DA in hospitality, as well as under-connected nodes that may indicate opportunities for future integration across research streams. Figure 6 displays the keyword co-occurrence network at the paragraph level. It acts as a proxy map to illustrate the clustering of topics evaluated in the literature. Bigger nodes represent more cited ideas, and thicker and darker linkages represent greater co-occurrence in the same text segments.

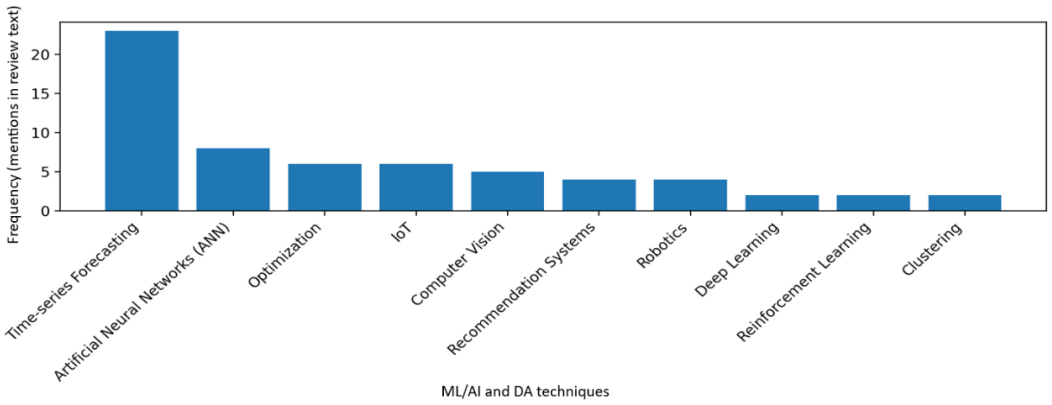


Figure 5. Frequency of ML/AI and DA techniques mentioned in the review text (proxy indicator)

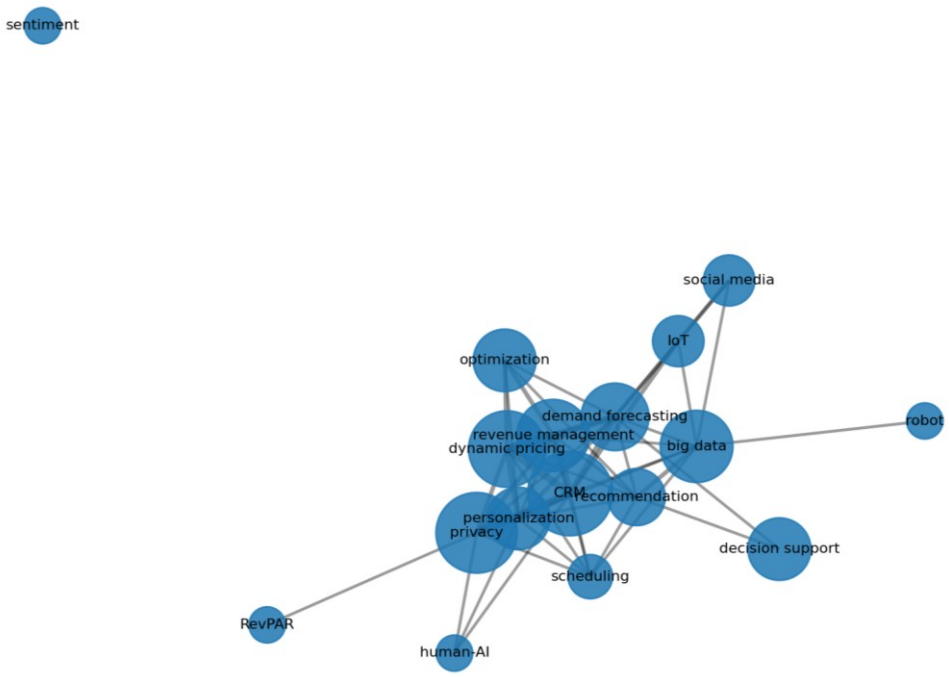


Figure 6. Keyword co-occurrence network in the included studies (paragraph-level proxy map)

Figure 7 illustrating relationships of core concepts across reviewed studies. The co-word links were calculated at the paragraph level, i.e., two terms are linked when they occur in the same paragraph. The size of each node shows the relative prominence of the corresponding keyword, and the thickness of links shows the strength of co-occurrence. The resulting structure highlights dominant thematic clusters (e.g., data-driven personalization, forecasting, pricing and RM, and decision support) and the intersections between these topics. Loose or periphery connections of nodes indicate niche or emerging streams. The network is intended to be reproducible with VOSviewer or Biblioshiny once the finalized dataset is applied.

Table 3 presents a systematic overview of the evidence base included in the review, with information on the composition of the evidence base by study type and on the temporal distribution of the retained studies. First, the typological analysis indicates that empirical/other studies constitute the largest group (46.7%), indicating that the field is strongly oriented towards application-driven studies, often involving the development, testing or implementation of models in the hospitality industry. However, the high proportion of review-based output such as literature reviews (28.9%), systematic reviews (20.0%), and bibliometric analyses (4.4%) shows that the domain is simultaneously in a process of consolidation and sense-making which is typical for fast-growing research fields with increasingly diverging methods and applications, outpacing the speed of theoretical integration.

Secondly, the distribution by year shows a strong recency effect. The evidence base contains a smattering of publications between 2009 and 2016, but the corpus grows substantially after 2022, with 2024 being the peak (40.0%) and 2025 still high (26.7%). The period 2024–2025 includes two-thirds of all included studies, indicating an increased scholarly attention in the most recent period. The rise in numbers of ML/AI applications seems to be driven by the wider availability of ML/AI, the rapid growth of digital data in the hospitality industry (e.g. CRM platforms, online reviews, and IoT) and increased demand from managers for decision-support systems.

Table 3 also indicates some methodological limitations in the classification approach. The "study type" category is based on a heuristic title-based coding procedure, which may misclassify mixed-method studies or papers in which the methodological approach is not explicitly stated in the title. Therefore, Table 3 should be interpreted as an informative overview rather than a definitive taxonomy. Overall, the evidence base suggests that the field is expanding empirically while also becoming increasingly self-reflective through synthesis-oriented scholarship.

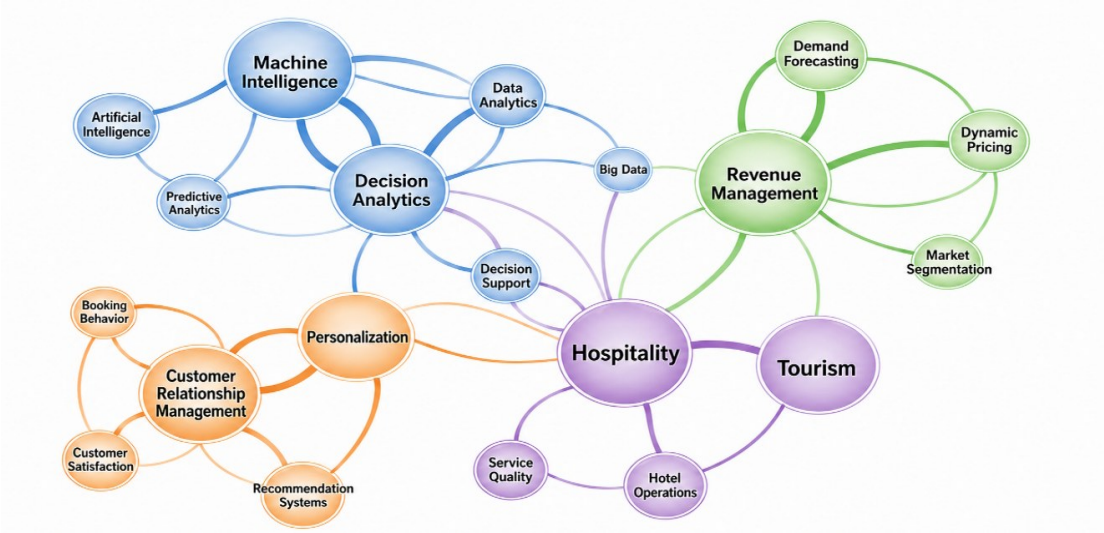


Figure 7. Keyword co-occurrence network (co-word links computed at paragraph level; reproducible in VOSviewer/Biblioshiny using the finalized dataset)

Table 3. Evidence-base composition by study type (heuristic classification from titles)

| Category | Item | Count | Share (%) |
|---|---|---|---|
| Study type | Empirical/other | 21 | 46.7 |
| | Literature review | 13 | 28.9 |
| | Systematic review | 9 | 20.0 |
| | Bibliometric analysis | 2 | 4.4 |
| Year | 2009 | 1 | 2.2 |
| | 2010 | 1 | 2.2 |
| | 2014 | 1 | 2.2 |
| | 2015 | 1 | 2.2 |
| | 2016 | 1 | 2.2 |
| | 2021 | 1 | 2.2 |
| | 2022 | 2 | 4.4 |
| | 2023 | 7 | 15.6 |
| | 2024 | 18 | 40.0 |
| | 2025 | 12 | 26.7 |

In fact, the discussion on staff and system acceptance of big data analytics and computer-based solutions refers to the challenges of employee adoption and process change inherent in the implementation of big data and other systems. Changing the role of employees and managers as a result of the new technologies was best summarized by a report on the use of big data at the hotel chain. Our most significant challenge involved changing our employees' relationship with data. It used to be the case that insights into our guests were intuited or rolled up in periodic reports to corporate [34]. So, we had to convince our employees that maybe the data is right, and their intuition is wrong. Technology being used means we have information at our fingertips at the right time with the ability to contextualize it based on real-time events. This automatically brings about a change to the process and the roles.

For the near future, a wide range of technological advancements are expected to revolutionize the hospitality industry. Many believe that AI will continue to develop, with smarter machines and predictive modeling algorithms able to significantly enhance decision-making for the industry. The automation of such decision-making by means of automated decision systems will continue to evolve to carry out updated scorecards, job scheduling, inventory management, maintenance, and much more in hospitality operations. Other trends anticipated include the increasing role of the IoT in the delivery of service to customers, while big data will continue to provide more data to help with decision models and, as a result, help manage resources more effectively. An interesting future trend is the continuation of personalized marketing by means of personalized recommendation engines and chatbots with the aim of providing a customized product to the customer, while advancements in personalized operations systems aim to provide operations targeting individual customers such as hotel rooms and housekeeping.

The impact of this will be massive [35]. There is no doubt that the capabilities that will soon become available will redefine the sector, leading to a completely different operating environment. Manual decision-making offers neither speed nor the quality of decisions that is becoming obligatory in the face of modern-day business competition. AI, ML, and systems capable of automating decision-making processes will soon become industry standards. Any hospitality company resistant to these changes in decision-making will miss out on a quantum leap in the capability of the industry. Because of these technological developments, high-quality jobs will continue to shift toward dominance in qualitative aspects, responsible innovation, ethical provision, capability, and adaptability. Concern is already being raised about the ethical implications of automation and decision support systems, which is something to consider. For example, the safety implications of the automation of managed innovations in the systems and properties of organizations, or the privacy-political hazards of automation or the unapproved use of surveillance, risk assessment, and control. Industry professionals are already pioneering these advancements [28].

Table 4 presents a brief overview of major empirical and review studies related to AI applications in the tourism and hospitality. Noor *et al.* [36] proposed an intelligent decision support system based on AI algorithms for the tourists to choose their destinations. However, it was limited to its set criteria and was not flexible with the real-time data. Cheng *et al.* [37] developed an intelligent mobile tourism service that combined smartphone GPS with Google Maps as an advanced navigation tool, but its usefulness was limited by the instability of the internet connection and the accuracy of the GPS. In the neurotourism insights study, Fajardo *et al.* [35] used eye-tracking and galvanic skin response (GSR) to demonstrate that men and women attend to and emotionally respond differently to destination brand logos and AI-generated images, providing new ideas for tourism branding. Buhalis and Law [38] gave a detailed e-Tourism review over two decades but its general focus on IT limited the coverage of AI-specific techniques. Sigala [39] review of social media analytics in crisis management in 2011 gave useful insights but only indirectly touched on AI technologies. Matusse *et al.* [40] did an analysis of search engine analytics to evaluate the online presence of Mozambican tourism websites. The results were insightful, but only focused narrowly on visibility metrics. Law *et al.* [41] did a survey of IT applications in hospitality, but AI applications were not much covered (2005–2005 to 2005–2007). Finally, Longhi *et al.* [42] discussed the role of open data in tourism innovation, providing some early information and communication technologies (ICT) perspectives, but with no relevance for further AI developments.

Table 2 summarizes previous works on destination decision support, mobile/context-aware services, neurotourism metrics for branding stimuli and broad IT/e-Tourism mappings. Re-structure these contributions by tool/technique, empirical scope, and limitations to emphasize where hospitality-specific MI/DA evidence is robust (e.g., demand forecasting/pricing) and where it is sparse (e.g., real-time field deployments and organizational adoption). As outlined in Table 4, prior work has tackled destination decision support, mobile/context-aware services, neuro-branding metrics and broader IT/e-Tourism mappings. We reorder them according to tool/technique, empirical scope and limitations to show where hospitality-specific MI/DA evidence is strong and where it is weak.

In summary, this review implies that data-aided DA and MI hold great potential to revolutionize the hospitality sector by enhancing guest experiences, optimizing operations, and fostering innovation in service design, especially in relation to CRM, RM, personalized marketing, and demand forecasting. Adoption of AI

is accelerating but integration is slow due to high costs, data protection concerns, ethical issues, data silos, lack of management expertise and resistance to change. Also, despite some promising applications of AI in predictive analytics and dynamic pricing, there are not many studies in the current literature that examine AI systems under real-time operational conditions. This makes it difficult to see how scalable, adaptable and long-lasting they will be. The study consolidates all the existing research, highlights regional variations, and identifies new opportunities such as metaverse-enabled pre-arrival experiences, thus advancing both theory and practice. It calls for closer cooperation between researchers, practitioners and policymakers in tackling problems of implementation, bridging gaps in knowledge and ensuring that the use of AI in hospitality is not only technologically advanced but also morally sound, financially sound and people-oriented.

This review aimed ultimately to answer three main questions: i) how is MI and DA applied in the hotel business today? ii) what are the major pros and cons of using them? and iii) what are the gaps in the literature and the focus of future study? The synthesis shows that MI and analytics can greatly enhance CRM, RM, personalized marketing, demand forecasting, and service innovation. However, high costs, data privacy issues, ethical dilemmas, siloed data, limited managerial expertise and employee resistance make it hard to integrate them. There have been advances in predictive analytics and dynamic pricing, but there is a scarcity of real-time deployment studies that assess AI systems in real-world contexts. This leaves open the questions of scalability, flexibility and long term effect [43]–[49]. The assessment offers a strategic basis for bridging these gaps, mapping current uses, identifying geographical differences and highlighting opportunities such as pre-arrival experiences in the metaverse. Researchers, practitioners and governments must work together to ensure that the adoption of AI in hospitality is not only technologically advanced but also ethically sound, financially feasible and people-centric.

Table 4. Summary of representative AI/MI applications in tourism and hospitality

| Authors | Tools/techniques | Findings | Limitations |
|---|---|---|---|
| Noor *et al.* [36] | AI algorithms for decision support | Developed a system to assist tourists in selecting destinations based on preferences | Limited to predefined criteria; may not account for real-time data |
| Cheng *et al.* [37] | Integration of GPS with Google Maps | Created a mobile travel agent system combining GPS and Google Maps for enhanced navigation | Dependent on internet connectivity and GPS accuracy |
| Fajardo *et al.* [35] | Eye-tracking and GSR analysis | Identified gender differences in emotional responses to tourism branding; utilized AI-generated visuals | Focused on branding; may not generalize to other tourism aspects |
| Buhalis and Law [38] | Information technology integration in tourism | Comprehensive review of e-Tourism research over two decades | Focuses on IT broadly; limited emphasis on AI-specific applications |
| Sigala [39] | Social media analytics | Examines the role of social media in crisis management within tourism | Primarily centered on social media; indirect focus on AI |
| Matusse *et al.* [40] | Search engine analytics | Analyzes the online visibility of destination marketing organizations | Limited to search engine visibility; does not delve into broader AI applications |
| Law *et al.* [41] | IT applications in tourism | Reviews IT applications in tourism and hospitality sectors | Covers a broad range of IT applications; limited focus on AI |
| Longhi *et al.* [42] | ICT in tourism | Discusses the impact of ICT on innovation in travel and tourism | Early study; predates significant AI developments in tourism |

### 4.2. Critical appraisal of studies

A critical appraisal of methodological quality was conducted to provide context for strength of evidence. Each included study can be scored high/medium/low using the rubric in Table 5. Quality criteria focus on i) robust evaluation (e.g., appropriate cross-validation or out-of-sample testing, baseline comparisons, and uncertainty reporting), ii) transparency and replicability (clear data description and, where possible, data/code availability statements), and iii) external validity (real-world datasets, multi-site settings, and clearly defined managerial outcomes). Three recurring weaknesses characterize the overall evidence base: i) overreliance on simulations and small-sample models, ii) limited external validation, and iii) incomplete reporting of cross-validation/benchmarking. Future work should focus on transparent data pipelines, standardized evaluation protocols, and field-level causal designs when feasible. This table offers a structured rubric to rate the methodological quality of the reviewed studies and directly relates to three recurring weaknesses in the evidence base: heavy reliance on simulations and small samples, limited external validation, and incomplete reporting of cross-validation and benchmarking. Quality is operationalised across four dimensions in the rubric. Model evaluation distinguishes studies that demonstrate rigorous generalizability (out-of-sample testing with cross-validation, explicit baselines, and uncertainty reporting) from those that depend on in-sample performance or unclear validation, which can inflate results and reduce

transferability [50]–[54]. Data transparency assesses how well datasets and variables are described so that they can be replicated or at least audited, a necessary condition for cumulative science and responsible deployment. Sample adequacy concerns statistical and contextual representativeness, rewarding multi-site or multi-dataset designs and penalizing small, unjustified convenience samples that are common sources of bias and instability. In terms of practical validity, it concerns whether models are tested in realistic operational settings and there are key performance indicators actionable KPIs to be acted upon. This makes the difference between decision support to be deployed and pure simulations.

Table 5. Quality appraisal rubric for included studies

| Criterion | High | Medium | Low |
|---|---|---|---|
| Model evaluation | Out-of-sample test + cross-validation; clear baselines; uncertainty reported | Either CV or hold-out; limited baselines | No clear validation; in-sample only |
| Data transparency | Data/variables described in detail; access/sharing statement provided | Partial description; limited reproducibility details | Opaque data source; insufficient description |
| Sample adequacy | Multi-site/large sample or multiple datasets; power considerations | Moderate sample; single site | Small or convenience sample without justification |
| Practical validity | Deployment or realistic operational setting; actionable KPIs | Prototype/partial realism | Pure simulation; no operational grounding |

## 5. CONCLUSION

The research concludes that data-driven DA and MI have significant potential to enhance purchasing, operations, marketing, service delivery and overall guest experience in the hospitality sector. CRM, RM, personalized marketing, demand forecasting, dynamic pricing, booking-cancellation prediction, complaint handling, and service innovation are among the areas where AI and ML applications are gaining traction. These technologies have the potential to increase operational efficiency, reduce staff workloads, facilitate data-driven decisions, and provide more personalized guest services. However, the broader penetration of AI in hospitality is constrained by various factors such as lack of managerial and technical knowledge, HR shortage, unequal access to advanced technologies, and high costs of implementation, as well as data security, privacy and ethical use. Smaller hotels may face financial challenges in investing in software, hardware, infrastructure, and staff training necessary for AI adoption. Also, hospitality companies have to strike a balance between personalization and privacy protection to avoid intrusive practices and maintain customer trust. The study also points out notable gaps in literature. However, there is still a lack of real-time studies based in the field of AI systems in real hospitality environments. There is also limited evidence on scalability, flexibility, long-term performance, and causal effects on customer lifetime value, churn and brand equity. On a regional level, there are also differences in AI adoption, with China and the United States leading the way and regions such as the Gulf Cooperation Council (GCC), Portugal, Spain, and the United Kingdom moving at a slower pace. Hence, future studies should focus on studies involving real-time deployment, A/B testing, and quasi-experimental designs, especially at the booking and pricing touchpoints. There is also a need for more collaboration between researchers, data scientists, policymakers and hospitality practitioners to devise scalable, ethical, cost-effective and human-centered AI solutions.

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This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

| Name of Author | C | M | So | Va | Fo | I | R | D | O | E | Vi | Su | P | Fu |
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| Rami Mahmoud | ✓ | | ✓ | ✓ | ✓ | | ✓ | | | ✓ | | | ✓ | |

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

## CONFLICT OF INTEREST STATEMENT

The authors declare that they have no known competing financial or non-financial interests that could have influenced the work reported in this paper.

## INFORMED CONSENT

This section is not applicable, as this study did not involve human participants or the use of identifiable personal data.

## ETHICAL APPROVAL

This section is not applicable, as this study did not involve human participants or animal subjects.

## DATA AVAILABILITY

The authors confirm that the data supporting the findings of this study are available within the article.

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