Artificial Intelligence And Emerging Tools For Pricing Optimization In Hotel Revenue Management: Systematic Literature Review

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Abstract

Artificial intelligence (AI) and advanced analytics are reshaping hotel revenue management (RM), with forecasting and pricing optimization as central levers of profitability. This paper presents a systematic literature review (2021-2025) of empirical research on AI and data-driven approaches in RM, conducted using the PRISMA framework and searches across Web of Science and Google Scholar. The reviewed studies show that the majority of research focuses on demand forecasting using deep learning, neural networks, and hybrid time-series models, while dynamic pricing applications remain less explored. Empirical evidence also highlights the integration of risk modeling, consumer psychology, and perceptions of price fairness, emphasizing the need to account for behavioral and ethical dimensions in pricing strategies. In parallel, scholars increasingly stress the importance of transparency and co-intelligence between algorithms and human analysts, moving beyond opaque „black box“ systems toward more interpretable and trustworthy solutions. Despite these advances, evidence directly linking AI tools to hotel performance indicators such as RevPAR, ADR, or guest satisfaction is still scarce, with many studies based on simulations or single-hotel cases. Overall, the review identifies forecasting as a relatively mature field, while AI-driven pricing remains a critical research gap. These findings provide both a roadmap for future inquiry and practical guidance for hotels seeking to leverage AI responsibly in their revenue strategies.

Keywords: dynamic pricing; forecasting models; hotel performance; machine learning; revenue strategy

1. Introduction

The hospitality industry represents a vital component of the global economy, contributing significantly to both growth and employment. In 2024, the Travel & Tourism sector generated USD 10.9 trillion, accounting for 10% of global GDP, while supporting 357 million jobs worldwide (WTTC, 2024). Given this scale, understanding hotel operations is crucial due to their perishable inventory and unpredictable demand. RM originated in the airline industry in the late 1970s to optimize revenue from fixed capacity under uncertain demand and was soon adopted by hotels, where unsold rooms represent lost income (Kimes, 1989; Cross, 1997). RM has evolved into dynamic, data

driven systems that integrate forecasting, pricing, and inventory optimization (Talluri & Ryzin, 2005; Weatherford & Kimes, 2003). As data analytics became central to revenue optimization, technological innovation paved the way for the next major step – the integration of intelligent systems. AI systems, capable of learning, reasoning, and decision-making (Bellman, 1978; Ivanov & Webster, 2017), now enable hotels to process vast datasets in real time, uncover demand patterns, forecast occupancy, and generate dynamic price recommendations beyond human capability.

While AI-enhanced forecasting has become relatively well established, the application of AI to pricing optimization remains underexplored. Most existing studies focus on improving demand predictions through neural networks, hybrid models, and other machine learning techniques, while fewer examine how these tools translate into optimal pricing strategies or measurable improvements in hotel performance indicators such as RevPAR or ADR. Moreover, ethical concerns about transparency and perceived fairness introduce further complexity to algorithmic pricing.

Although there is a growing interest in the adoption of AI tools within hotel RM, existing systematic reviews predominantly address demand forecasting or general AI applications in hospitality rather than AI-driven pricing optimization. To contribute to this under-explored area, this study applies the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) protocol to systematically review literature published between 2021 and 2025 that focuses on AI tools for pricing in hotel RM. The paper integrates findings on AI-driven forecasting and pricing, highlighting key methodological trends, managerial implications, and ethical considerations shaping the future of RM. The purpose is to provide a comprehensive synthesis of recent research, identify areas of theoretical advancement, and evaluate the extent to which these developments are supported by empirical evidence.

Accordingly, the study aims to: (1) trace the evolution of AI-driven forecasting and pricing within hotel RM; (2) assess how ethical, behavioral, and managerial dimensions are incorporated into AI applications; (3) critically contrast the scarcity of academic evidence linking AI to performance indicators (RevPAR, ADR, occupancy) with concrete success stories from industry adoption; and (4) identify major research gaps and propose directions for future research.

In line with these aims, the review is guided by the following research questions:

RQ1: How has AI transformed forecasting and pricing processes within hotel revenue management?

RQ2: How are ethical, behavioral, and managerial dimensions reflected in the design and adoption of AI-based revenue management systems?

RQ3: What conceptual and methodological gaps remain in the literature, and how can future studies address them?

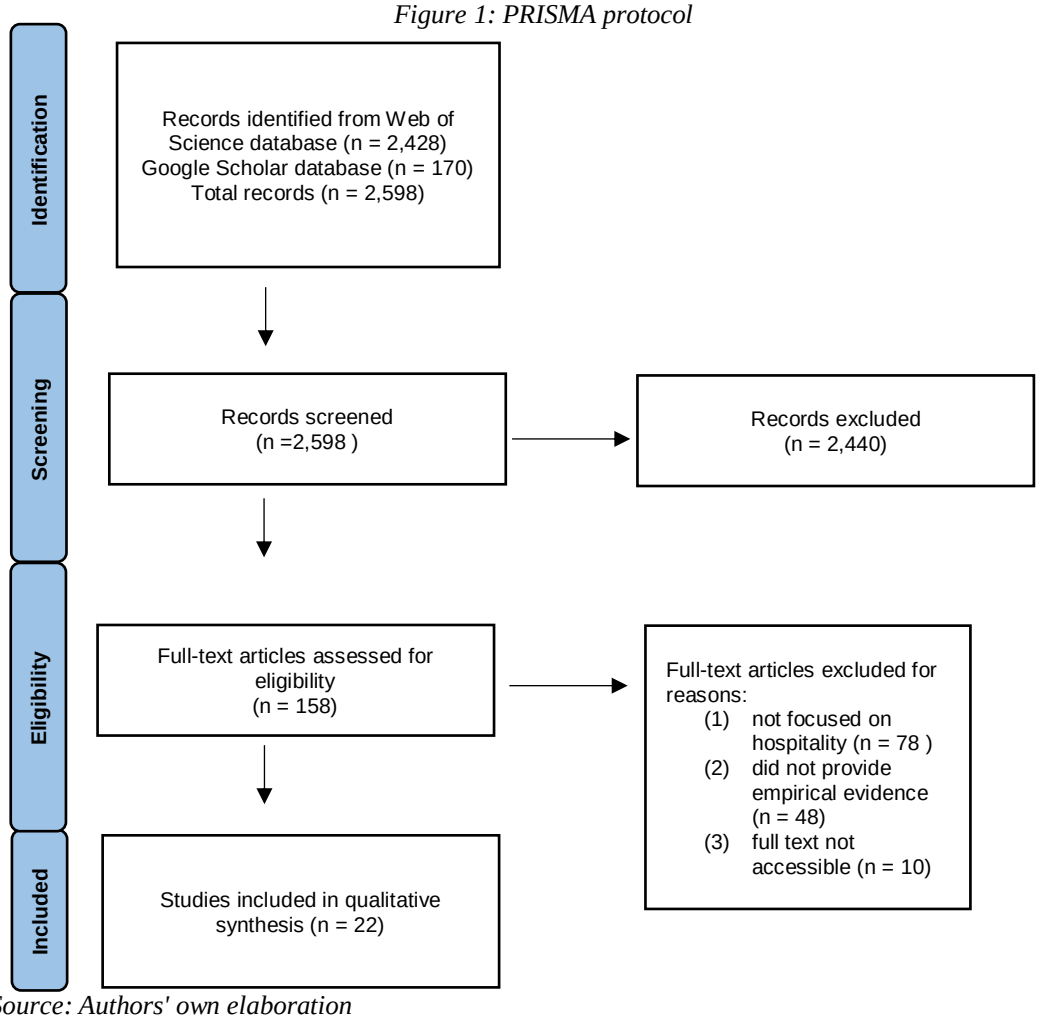
2. Methodology

This review follows the PRISMA guidelines to ensure transparency and replicability. Two databases were selected: Web of Science, as the primary source of high-quality peer-reviewed research, and Google Scholar, as a supplementary source to capture interdisciplinary studies.

The search strategy combined keywords across three thematic areas: (1) artificial intelligence ("artificial intelligence", "AI", "machine learning"); (2) pricing and revenue management ("pricing optimization", "revenue management system"); and (3) hospitality ("hotel", "hospitality", "hotel prices"). Boolean operators were applied to refine search. The search was restricted to the contemporary period of 2021-2025.

The initial search identified 2,598 records. After removing duplicates, non-peer-reviewed materials, conference proceedings, editorials and book chapters, and filtering by relevant subject categories (Hospitality, Leisure, Sport & Tourism), 158 full-text articles were assessed for eligibility. Articles were excluded based on three primary criteria: (1) they did not specifically focus on the hotel industry, (2) they lacked empirical evidence; or (3) full text was not accessible. Following this systematic process, 22 studies met all inclusion criteria and were integrated into the final qualitative synthesis. The detailed flow of the screening and selection process is illustrated in the PRISMA flow diagram (Figure 1).

Figure 1: PRISMA protocol

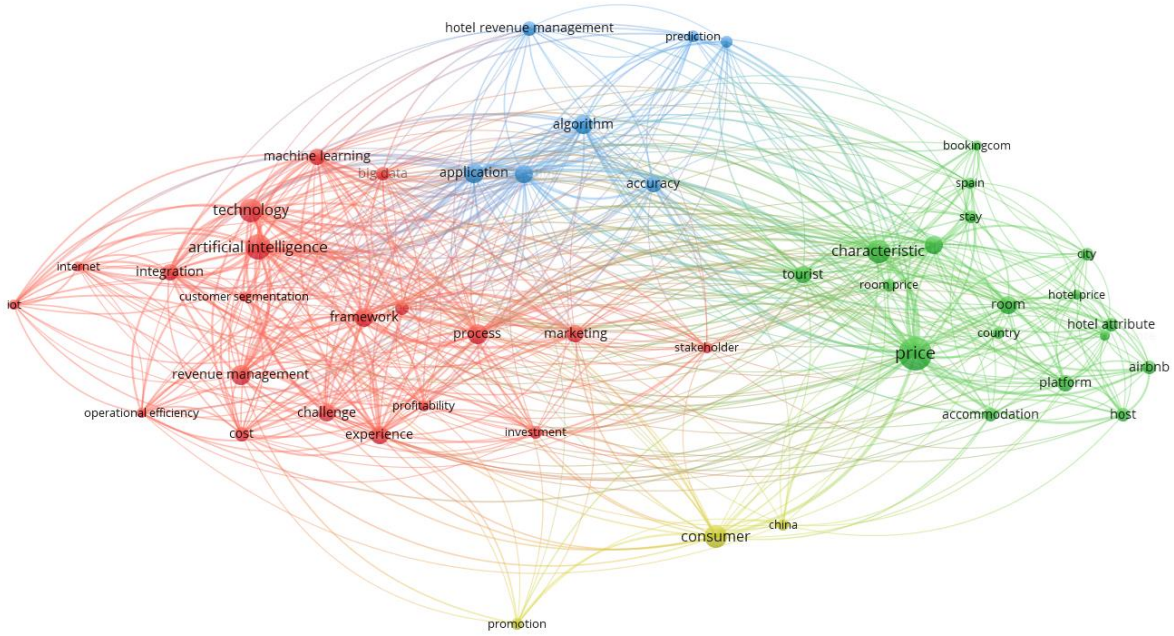


Source: Authors' own elaboration

To map the research landscape and validate the thematic structure of this review, a VOSviewer co-occurrence analysis of terms from titles and abstracts was performed, identifying four thematic clusters (Figure 2).
With the highest link strength, red cluster represents the strategic core of the literature, framing AI as an integral part of broader revenue management systems (RMS). Green cluster focuses on external market determinants of hotel pricing, such as location and

competitive environment. Blue cluster captures methodological contributions, emphasizing algorithms, forecasting methods, and prediction accuracy, serving as the core computational foundation. Yellow cluster is a low-density stream pointing to consumer-focused, ethical, and regional studies, suggesting an emerging research focus.

Figure 2: The network visualization of the most used terms



Source: Authors' own elaboration

The VOSviewer analysis visually confirms the primary research gap of this review. While the map is highly dense around algorithmic concepts and strategic implementation, the complete absence of key performance metrics such as RevPAR, ADR, or profitability from the co-occurrence analysis underscores the existing scholarly deficit. This demonstrates that the academic focus is disproportionally centred on the internal mechanic of AI (methodology), rather than providing robust empirical evidence of its measurable commercial impact on key hotel performance indicators.

3. Findings

The reviewed studies show varied AI applications in hotel RM. Table 1 provides a summary of the selected empirical papers, outlining their research context, data and methods, RM focus, and key findings. This overview establishes the foundation for the thematic synthesis presented in the following sections.

Table 1: Literature review

No.	Author(s)	Location, Sample	Data, Method	RM focus	Key findings
1	**Binesh et al. (2023)**	U.S. – 3 hotels - (2018-2020)	STR data; LSTM neural network with game-theoretic and risk metrics; compared with ARIMA and regression models	ADR forecasting under crisis (AI: yes)	LSTM outperformed traditional models, especially in volatile periods. Including competitor and risk data improved stability.

2	**Webb et al. (2024)**	multi-country – 35 hotels (2016-2019)	RMS booking data; compared k-NN and ANN (MLP); 1,050 variants tested	Demand forecasting (AI: yes)	ANN was slightly more accurate, but k-NN easier to interpret and better suited for hotels with limited expertise.
3	**Schwartz et al. (2021)**	global - 900 hotels (2013-2016)	Panel regression and experiments on algorithmic vs. human overrides	Forecast accuracy & human-AI combination (AI: yes)	Combining AI with human input improved accuracy, especially for long-term forecasts; the effect declined as both learned.
4	**Qiu et al. (2021)**	Hong Kong –5 hotels (2019 social unrest)	STR data + Twitter crisis indicators; SARIMA, ETS, STL, SARIMAX, ETSX, STLX	Occupancy forecasting during crisis (AI: yes)	Adding social media signals increased accuracy during unrest, especially for luxury hotels; traditional models stabilized later.
5	**Ampountolas (2021)**	Boston, U.S. - 1 hotel (2015-2019)	Daily demand; SARIMAX, ANN-MLP, sGARCH, ARIMA, Holt-Winters	Forecasting daily demand (AI: yes)	SARIMAX performed best; competitor rank was a key external predictor.
6	**Ampountolas & Legg (2025)**	U.S. – large hotel chain (2015-2019)	200k+ bookings; ML models (RF, XGBoost, LightGBM, ANN-MLP)	Cancellation forecasting (AI: yes)	ANN-MLP most accurate, especially short-term; OTA and short lead times strongest predictors. LightGBM effective for longer-term forecasts.
7	**Gómez-Talal et al. (2025)**	Southern Europe – 1 hotel (2 years)	Booking data; stacking meta-model (RF, XGBoost, LightGBM, MLP); SHAP	Cancellation forecasting (AI: yes)	Meta-model reached 96% accuracy; SHAP analysis identified key drivers (country of origin, lead time, room type, deposit type), enabling interpretable and ethically transparent insights.
8	**Ampountolas & Legg (2021)**	U.S (2016-2019)	PMS data and social media sentiment; XGBoost vs. ARIMA and Naïve; hierarchical clustering	Occupancy forecasting using sentiment (AI: yes)	XGBoost outperformed benchmarks. Including sentiment data improved long-term forecast accuracy and model robustness.
9	**Kouprioucchina et al. (2022)**	global – 1,752 hotels (2014-2017)	RMS data; multilevel regression; 7 forecast horizons; override frequency analysis	Forecasting accuracy & judgmental adjustments (AI: yes)	Accuracy improved closer to stay date. Human overrides enhanced group forecasts but reduced transient accuracy; useful during special events.
10	**Chalupa & Petricek (2024)**	Prague, Czech Republic - 1 hotel	Opera PMS data; Two-Step Cluster Analysis (7 variables) and regression for elasticity	Price elasticity by segments (AI: yes)	Six customer clusters identified with distinct elasticities, supporting targeted pricing and promotion strategies.
11	**Roma et al. (2021)**	Italy – 3,047 hotels (Mar-May 2018)	Booking.com data; two-way random effects regression; Airbnb penetration (AirDNA)	Market-level pricing & competition (AI: no)	Airbnb penetration reduced prices in 1-3* hotels, but increased them in 4-5* properties; effects varied by market segment.
12	**Arzaghi et al. (2023)**	Dubai, UAE – 250 hotels; (Mar 2020)	Booking.com data; hedonic OLS regressions with spatial clustering	Price determinants & local competition (AI: no)	Prices increased with size, quality, and central location, but nearby competition reduced rates; local clustering significant.
13	**Bigne et al. (2021)**	Spain – 1,085 hotels (2012-2014)	39,363 reservations; Two-Stage Least Squares regression	Channel-based pricing (AI: no)	Advance booking increased rates. OTA and direct rates converged 30 days before the stay; GDS channels showed the lowest early prices.
14	**Zaki (2022)**	Cairo, Egypt – 31 hotels (Jun-Dec 2020)	Mixed-methods: Value Stream Mapping, DEA, Wavelet Analysis; 200 survey respondents + expert interviews	RM model development & efficiency (AI: no)	Created 6-phase RM model linking dynamic pricing to efficiency. Found short-term gains during crisis but weak long-term effects.

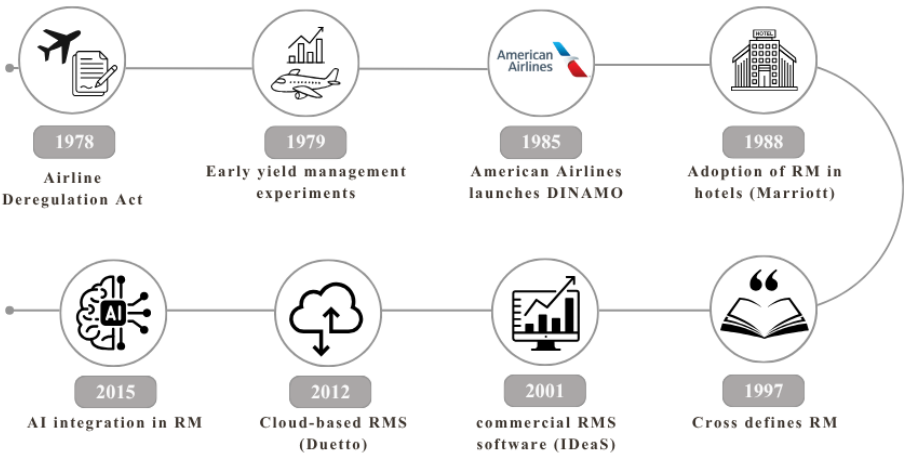
15	**Battiti et al. (2021)**	simulation study (synthetic hotel data)	Simulation of LOS distributions and seasonal scenarios; algorithms tested: Random, FirstFit, MinSlack, MaxSlack, RoomTetris	Room allocation optimization (AI: no)	RoomTetris algorithm improved occupancy and reduced rejections without MLOS rules; increasing revenue in high-demand periods.
16	**Erdmann et al. (2024)**	Germany and Spain – 8 pricing experts	Multi-criteria decision-making (Fuzzy BWM + Fuzzy CoCoSo; 9 stakeholder criteria vs. 8 AI-supported pricing functions	AI adoption prioritization in pricing (AI: yes)	Accuracy, reliability, customer value, and efficiency are top-ranked criteria. Personalized pricing rated lowest due to ethical concerns.
17	**Ivanov et al. (2021)**	Italy – 248 hotels (Feb-May 2019)	Online survey; cluster analysis; non-parametric tests	Adoption of RM practices (AI: no)	Large, urban, chain hotels use RM tools more. Pricing tools more common than non-pricing; RMS use still rare.
18	**Takuatung & Bussracumpakorn (2024)**	Bangkok, Thailand – 2 hotels (2016-2021)	Mixed methods: interviews + OTA/direct booking data; K-means clustering, logistic regression, decision trees	Segmentation & automation for small hotels (AI: yes)	Lightweight AI tools improved segmentation and pricing decision, but full RM integration still required operational data.
19	**Meatchi et al. (2021)**	France – 32 interviews; 343 + 325 survey respondents	Mixed-methods: Critical Incident Technique + Lexicometry (Iramuteq); PCA + PLS-SEM	Perceived price fairness (AI: no)	Developed 3D unfairness scale: (normative deviation, opacity, negative affect). Showed emotional reactions can lower willingness to pay.
20	**Kim et al. (2021)**	U.S. – 797 participants (Jun-Jul & Dec 2020)	Five studies (surveys + experiments) + Google Trends analysis; regression, ANOVA, mediation	Consumer behavior under crisis (AI: no)	During COVID-19, consumers preferred higher-priced hotels for perceived safety; budget hotels should emphasize quality, not discounts.
21	**Zhang et al. (2023)**	Kuqa, China– 1,710 survey respondents	Discrete Choice Experiment; Error Components model; three treatments (Free, ¥1 token, Discount)	Psychological/ Promotional pricing (AI: no)	Confirmed Zero Price Effect: free promotions strongly increased demand even when total price unchanged.
22	**Lee & Schwarma (2025)**	U.S. – 573 participants (online booking scenarios)	Experimental design (3x2 factorial: Ota vs. direct, price parity variations)	Booking behavior under price parity (AI: no)	Price parity encouraged direct bookings; when prices differed, OTA flexibility and credibility shifted preferences toward OTAs.

Source: Authors' own elaboration

The reviewed literature confirms the continuous evolution of hotel RM from its origins in rule-based capacity control toward data-driven and adaptive systems supported by AI. Early RM practices, rooted in forecasting and overbooking strategies, have gradually expanded to include dynamic pricing, segmentation, and channel management as digitalization reshaped competitive dynamics. The empirical studies reviewed in this paper illustrate how this progression has culminated in AI-enhanced models capable of processing real-time data, integrating external signals, and supporting predictive decision-making. Most research focuses on forecasting accuracy—particularly demand and cancellation predictions using deep learning, neural networks, and hybrid time-series models—which consistently outperform classical approaches such as ARIMA or exponential smoothing. Although forecasting remains the most developed area, relatively fewer studies extend these capabilities to dynamic pricing or measure their direct financial impact. The literature also shows that AI adoption varies across contexts: large chains lead in the use of integrated RMS, while smaller hotels rely on simplified or hybrid approaches. Across studies, there is growing emphasis on interpretability, managerial trust, and ethical transparency, reflecting a shift from purely technical optimization toward the alignment of analytics,

human expertise, and responsible decision-making. Taken together, these findings depict RM as a discipline in transition—evolving from manual, experience-based practice to intelligent, data-driven systems that balance automation with human judgment.

Figure 3: Evolution of Revenue Management



Source: Authors' own elaboration

4. Emerging theoretical themes

Building on the evolutionary development of RM and the patterns identified in recent empirical research, the following sections explore four interconnected areas through which AI is reshaping hotel revenue strategy. The first examines forecasting and cancellation modeling as the analytical core of RM, showing how machine learning enhances predictive precision while raising questions of interpretability and human–AI collaboration. The second focuses on pricing and elasticity, where data-driven insights are translated into dynamic rate decisions and contextual market responses. The third theme addresses AI adoption and integration, contrasting academic findings with industry evidence to highlight practical outcomes and persistent gaps in technological readiness across hotel types. Finally, the behavioral and ethical dimensions of pricing consider how transparency, fairness, and trust influence both managerial acceptance and guest perception of algorithmic pricing. Together, these themes illustrate the multifaceted transformation of RM into an intelligent, ethically informed, and strategically adaptive discipline.

4.1 Forecasting and Cancellation Modeling

Among the thematic areas reviewed, forecasting emerges as the most studied domain, reflecting its role as the foundation of pricing and broader RM. The reviewed studies illustrate both the progress and the limitations of AI-driven forecasting in hospitality. Across different contexts—from single-property case studies (Ampountolas, 2021) to large-scale multi-country datasets (Webb et al., 2024)—a consistent finding is that advanced machine learning models such as LSTM, ANN-MLP, and ensemble meta-models substantially outperform traditional benchmarks like ARIMA, exponential smoothing, or SARIMAX when demand is volatile or cancellations are high (Binesh et al., 2023; Ampountolas & Legg, 2025; Gomez-Talal et al., 2025). Particularly in periods of disruption (COVID-19, social unrest), deep

learning models capture nonlinearities better than traditional time-series models (Qiu et al., 2021).

However, accuracy alone does not determine practical value. Studies that compared opaque neural networks („black-box“ models) with more interpretable approaches (e.g., k- nearest neighbor; k-NN) underline the need to balance performance and transparency (Webb et al., 2024). While complex ANN structures often deliver marginally higher accuracy, simpler or „glass box“ models can be more easily trusted and adopted by managers, especially in properties without advanced RMS. In this sense, the literature resonates with the broader concept of co-intelligence—the view that the most effective outcomes arise when algorithmic forecasts and human expertise are combined (Erdmann et al., 2024; Schwartz et al., 2021; Webb et al., 2024).

Another insight concerns the role of contextual and behavioral signals. Incorporating external data such as competitor ADR (Binesh et al., 2023), OTA booking characteristics (Ampountolas & Legg, 2025), or even social media sentiment (Qiu et al., 2021) systematically improves forecast robustness. Cancellation forecasting studies further underscore this: models using granular booking-level data (lead time, deposit type, country of origin) reach very high predictive accuracy (up to 96%) and provide interpretable drivers through SHAP analysis (Gomez-Talal et al., 2025), suggesting that cancellations can be predicted not only with precision but also in ways that generate actionable insights.

Forecasting research is shifting from pure accuracy toward more integrated and interpretable models. Even though accuracy gains are clear, direct links between these improved forecasts and actual revenue uplift are rarely measured, representing a critical gap for future research. Building on these forecasting insights, the next section examines how such predictive capabilities translate into actual pricing decisions.

4.2 Pricing and Elasticity

While forecasting provides the analytical foundation of RM, translating predictions into optimal pricing decisions remains the more complex and less explored domain. Pricing studies in hospitality consistently highlight that accurate demand forecasts must be complemented by models that capture market determinants, distribution effects and consumer response. Recent empirical research points to a transition from static, rule-based rate setting toward AI-enhanced and data-driven approaches capable of learning from booking behavior and contextual factors. Dynamic pricing has become the dominant strategy, but its effectiveness depends on how well algorithms account for elasticity.

Importantly, the literature reveals a clear distinction in the adoption of AI-driven pricing tools between large hotel chains and smaller, independent properties. Large and urban hotels consistently implement advanced revenue RMS, leveraging dynamic pricing strategies, big data analytics, and proprietary algorithms to optimize pricing decisions. These properties benefit from greater resources, technical expertise, and operational scale, enabling them to manage complex pricing structures and multiple distribution channels effectively. In contrast, small and boutique hotels often rely on traditional or opaque pricing methods due to limited financial and human resources. The absence of dedicated revenue managers and the high cost of implementing sophisticated AI tools present significant barriers. However, simplified machine learning models—such as k-NN, which can be implemented in tools like Excel—offer a practical alternative for

these properties, enabling them to enhance pricing decisions without full-scale RMS integration.

Evidence from large-scale datasets (Bigne et al., 2021; Roma et al., 2021) demonstrate that price sensitivity is dynamic and context-dependent, varying across booking windows, distribution channels, and market segments. OTA channels exhibit higher elasticity and greater short-term volatility, while direct bookings display more stable patterns closer to arrival. Roma et al. (2021) further discuss how the growing penetration of peer-to-peer accommodation platforms (e.g. Airbnb) exerts asymmetric price pressure: reducing rates for lower-rated properties while reinforcing rate resilience among upscale hotels. At the property level, Chalupa & Petricek (2024) applied machine learning–assisted clustering and elasticity modeling to nearly 10,000 bookings, revealing inelastic behavior for most guests, with a few highly price-sensitive clusters requiring dynamic elasticity calibration.

Further contributions extend the analysis to operational and ethical dimensions. Zaki (2022) found that dynamic pricing enhanced short-term efficiency during crisis conditions but lacked robustness over prolonged volatility, echoing forecasting studies that reported declining model stability in disruptive contexts (Ampountolas & Legg, 2025). Takuatung & Bussracumpakorn (2024) showed that even lightweight AI applications can automate short-term segmentation and pricing with measurable efficiency gains, though integration with forecasting and inventory optimization remains partial. Together these studies reinforce the need for interpretable, human-AI collaboration frameworks, where analytical performance is balanced with managerial trust and consumer confidence. As the literature on pricing continues to evolve, attention increasingly shifts from conceptual modeling toward practical implementation —namely, how AI-powered systems operationalize these insights within real hotel environments.

4.3 AI Adoption and Integration

The analysis of performance indicators reveals a significant scholarly deficit. Academic research often focuses on algorithmic efficiency, but rarely documents the real-world impact of AI tools on hotel performance. In contrast, industry reports and commercial case studies —often published by leading RMS providers such as Duetto, IDeaS, BEONx—offer concrete evidence of success, including measurable improvements in key performance indicators like RevPAR and ADR. This gap highlights the need to study the tools that are widely used in practice. Among the most prominent AI-powered RMS are Duetto, IDeaS, BEONx, and FLYR, each offering advanced capabilities for demand forecasting, price optimization, and segmentation. More hotel groups are adopting these systems to replace manual pricing with smarter, automated solutions.

Recent academic research has sought to assess both the theoretical frameworks and practical implementation of AI-supported price functions (AISPF) in hospitality. Erdmann et al. (2024) developed a multi-criteria decision model based on expert evaluations from Germany and Spain, identifying nine stakeholder criteria for sustainable AI adoption in pricing. These include forecast accuracy, customer value enhancement, cost-efficiency, automation, ease of use, and legal aspects such as data protection and transparency. The study found that forecast accuracy and reliability, followed by customer value, were the most important criteria, while ethical and legal criteria were ranked lower by practitioners.

Supporting this, Ivanov et al. (2021) conducted an empirical study on 248 hotels in Italy, revealing a significant gap between academic recommendations and actual RM practices. While pricing tools like price differentiation and early bird rates are widely used, more advanced AI-supported functions such as overbooking optimization or dynamic segmentation remain underutilized. Only 12% of hotels had a dedicated revenue manager, and just 29% used RMS software, indicating that AI adoption is still limited—especially among small and independent properties. The findings highlight the need for targeted education and strategic investment in AI tools to bridge the research-practice gap.

In parallel, Takuatung & Bussracumpakorn (2024) explored the role of AI and machine learning in boutique hotel service digitalization in Thailand. Their study showed how predictive analytics and clustering algorithms can segment guests, forecast demand, and automate pricing decisions in real time. The implementation of contactless service platforms—enabled by AI—helped hotel owners reduce operational costs, improve guest experience, and eliminate manual RM tasks. This case illustrates the transformative potential of AI not only in pricing but also in service delivery and personalization, especially in post-COVID hospitality contexts.

These academic insights are reflected in several recent success stories. For example, Amanta Hotels in Bangkok transitioned from manual spreadsheet-based pricing to Duetto's GameChanger RMS. Within two months, the group reported a 21% increase in revenue and RevPAR at Amanta Ratchada, and 34% uplift at Amanta Sathorn—achieved solely thorugh smarter pricing and automation. Similarly, Jannah Hotels & Resorts in the UAE adopted Duetto across five properties and experienced a 22% increase in RevPAR and a 34% growth in ADR. Automated rate management and improved forecast accuracy enabled the team to respond more effectively to market changes while reducing manual workload.

On the BEONx side, CoolRooms Hotels—boutique group in Spain and Portugal—reported a 15-20% increase in total revenue after implementing BEONx RMS with Lighthouse analytics. Occupancy and ADR rose by 10- 20% compared to the previous year. Hotel Claridge in Madrid also adopted BEONx's RMS and recorded a 20% increase in ADR and a 10% rise in occupancy. Automation allowed the team to shift from manual tasks to strategic pricing decisions, improving market positioning and revenue.

From the IDeaS portfolio, Casa Angelina—a luxury boutique hotel on Italy's Amalfi Coast—achieved an 87% increase in RevPAR and a 78% uplift in ADR between 2019 and 2023 after implementing the IDeaS G3 RMS. The management credited the system's strategic recommendations and consulting support for helping them maintain pricing discipline and avoid unnecessary rate drops, even during low-demand periods.

Together, these findings confirm that AI tools are not only theoretically sound but also practically effective. They deliver measurable improvements in pricing precision, operational efficiency, and overall hotel performance. As AI tools become more widespread, questions about their ethical implications and perceived fairnes among managers and guests are gaining importance.

4.4 Behavioral and Ethical Dimensions of Pricing

Recent research has increasingly emphasized the behavioral and perceptual dimensions of revenue management pricing (RMP), shifting attention from technical

optimization to the psychology of fairness and consumer response. Although AI improves pricing accuracy, guest acceptance depends on transparency, fairness, and data privacy. Ethical implications are addressed by Meatchi et al. (2021) and Erdmann et al. (2024), who demonstrated that while AI-based pricing improves analytical precision, guest acceptance ultimately depends on transparency, perceived fairness, and respect for data privacy—issues equally relevant for algorithmic forecasting (Webb et al., 2024). Meatchi et al. (2021) developed a multidimensional framework for perceived unfairness in hotel pricing, identifying three drivers—normative deviation, opacity, and negative affect—that jointly explain why price changes can elicit anger, stress, or feelings of disrespect. Even if guests understand the logic behind price changes, they may still react negatively if the changes seem unfair or arbitrary. Such emotional dissatisfaction, as noted by Meatchi et al. (2021), can substantially reduce willingness to pay (WTP), making perceived fairness a strategic as well as ethical concern.

Behavioral studies confirm that context and external threats further shape how prices are perceived. Kim et al. (2021) show that during periods of heightened uncertainty, such as the COVID-19 pandemic, travelers associate higher prices with safety and reliability, exhibiting compensatory consumption behavior that prioritizes reassurance over savings. This shows that pricing sends both economic and emotional signals. Roma et al. (2021) add that competitive structure also mediates perception: in markets with strong Airbnb penetration, budget hotels respond with downward adjustments while upscale properties maintain or elevate rates to signal exclusivity. Transparency can help reduce perceptions of unfairness by showing how prices are set, but it rarely removes emotional resistance. This means that clear communication and ethical framing are essential for effective pricing.

At a micro level, Zhang et al. (2023) identify the Zero Price Effect—a robust behavioral bias whereby consumers disproportionately favour offers containing a “free” element, even when the overall economic value is unchanged. In hotel settings, “free breakfast” or “free night” promotions significantly increase booking likelihood through emotional framing rather than objective savings. This aligns with Chalupa & Petricek (2024), who found that “Product Seekers” display high elasticity and strong affective response to rate changes, underscoring the need for AI models that incorporate behavioral segmentation. Lee & Sharma (2025) expand this perspective internally, showing that even managers experience ambivalence toward algorithmic pricing: while acknowledging its analytical value, they often override system suggestions when outputs conflict with their intuitive sense of fairness.

Ethics and behavior are closely connected in pricing decisions. Erdmann et al. (2024) and Schwartz et al. (2021) argue that interpretability and human–AI collaboration—the so-called co-intelligence paradigm—are essential for sustaining both employee trust and guest confidence. Likewise, Zaki (2022) situates this debate in a post-crisis context, showing how the pandemic amplified demands for empathetic and socially responsible pricing. Collectively, these studies indicate that the future of hotel RMP depends less on algorithmic precision and more on its capacity to be understood, trusted, and perceived as fair. The integration of behavioral insights into AI-driven RMS offers a path toward ethically grounded, psychologically credible, and commercially effective pricing decisions. Together, these behavioral and ethical insights complete the multidimensional understanding of AI in RM, bridging algorithmic performance with human judgment and customer perception.

5. Discussion and future paths

This literature review highlights several key insights, among which the concept of co-intelligence stands out. This paradigm emphasizes the collaboration between algorithmic outputs and human expertise, supported by continuous monitoring of contextual and behavioral data. For example, detailed booking information such as the number of guests, booking time, and deposit type can be integrated into algorithms that are subsequently validated and supervised by human managers. The reviewed studies indicate that expectations regarding the use of AI in hospitality are notably high. These expectations extend beyond analytical efficiency to encompass strategic decision-making, particularly in synthesizing information and making context-aware judgments. Moreover, perceived usefulness emerges as one of the most influential factors shaping managers' decisions to adopt AI in business operations. Future research should therefore examine how adoption factors (such as perceived usefulness and compatibility) interact with firm-level capabilities (such as data readiness and human capital) to predict performance outcomes.

In parallel, AI-based pricing and forecasting systems are evolving toward self-learning, dynamic models that incorporate diverse inputs, including market conditions, consumer behavior, and competitor pricing. What was once technologically complex and financially inaccessible to smaller hotels is now becoming increasingly affordable due to the wider availability of AI applications. This development not only narrows the performance gap between large and small hotels but also enhances the business agility of independent and family-owned properties. Finally, recent studies emphasize the growing importance of designing AI systems that account for customers' perceptions of price fairness. Therefore, AI solutions aiming to build and sustain trust should be grounded in four key pillars: price fairness, transparency of business conditions, data reliability and security, and the preservation of human oversight.

Through the literature review, the authors propose answers to the research questions, which can be summarized as follows.

First RQ: How has AI transformed forecasting and pricing processes within hotel revenue management?

AI has fundamentally reshaped hotel RM by enhancing the analytical depth and predictive accuracy of forecasting and pricing systems. In this regard, AI has not replaced human expertise but has instead transformed it. The reviewed studies consistently demonstrate that machine learning approaches particularly deep learning models and ensemble meta-models outperform traditional time-series in conditions of demand volatility or high cancellation rates (Binesh et al., 2023; Ampountolas & Legg, 2025; Gómez-Talal et al., 2025). These models enable hotels to capture nonlinear relationships, integrate external signals such as competitor rates or social media sentiment, and generate more agile pricing responses. Practically, the integration of these advanced models empowers hotels to move from reactive pricing to proactive revenue strategies, thereby enhancing competitiveness and profitability. Moreover, optimal performance increasingly depends on human AI-collaboration, where algorithmic precision complements managerial intuition rather than replacing it (Schwartz et al., 2021; Erdmann et al., 2024). Interpretability and transparency also emerge as critical factors: studies comparing complex neural networks with simpler "glass box" models (Webb et al., 2024) show that managers often prefer models they can easily understand and justify.

Second RQ2: How are ethical, behavioral, and managerial dimensions reflected in the design and adoption of AI-based revenue management systems?

While technical performance is a key success factor, the reviewed studies highlight those ethical and psychological factors critically determine the acceptance and perceived legitimacy of AI in RM. Research by Meatchi et al. (2021) and Erdmann et al. (2024) shows that algorithmic precision alone does not ensure customer acceptance; transparency, fairness, and respect for privacy are equally important. Price opacity or unexplained fluctuations can trigger perceptions of unfairness, leading to emotional responses such as anger or distrust that undermine willingness to pay. From a managerial perspective, these ethical issues are mirrored in internal practices. Managers often override AI-generated recommendations when algorithmic outputs conflict with their intuitive sense of fairness or market logic (Lee & Sharma, 2025). This behavior underlines a persistent need for explainable AI and training programs that help revenue managers interpret model outputs confidently. Moreover, behavioral research demonstrates that contextual factors, such as crisis conditions (Kim et al., 2021) or competitive pressures (Roma et al., 2021) shape how both guests and employees perceive dynamic pricing. Consequently, the literature suggests that the future of AI-powered RM depends less on technical capability and more on trust, transparency, and ethical use. The integration of behavioral economics and ethical design into AI systems thus represents the next frontier of sustainable RM.

Third R3: What conceptual and methodological gaps remain in the literature, and how can future studies address them?

Despite clear progress, several conceptual and methodological gaps persist. First, the empirical evidence linking AI implementation to tangible hotel performance indicators (RevPAR, ADR, occupancy) remains scarce. Most academic studies rely on small samples, single-property cases, or simulated data, while large-scale or longitudinal evaluations are virtually absent. In contrast, industry case studies from Duetto, IDeaS, and BEONx report revenue uplifts between 15% and 35%, suggesting substantial research practice gap that future work should bridge.

Second, the literature lacks standardization in evaluating model performance and often prioritizes statistical accuracy over managerial relevance. Few studies assess how improved forecasts translate into measurable financial or strategic outcomes. Third, the theoretical integration of AI research remains limited, which restricts cumulative theory building. Most studies focus on technical performance rather than linking AI to broader concepts. Moreover, ethical and behavioral constructs are rarely operationalized quantitatively, leaving their actual impact on adoption and customer behavior underexplored.

In addition, while forecasting capabilities have advanced considerably, the application of AI to dynamic pricing remains underexplored. Most empirical research continues to prioritize improving demand prediction accuracy rather than translating these forecasts into revenue-maximizing pricing decisions. Future studies should therefore examine hotel performance over longer periods and across diverse property types, enabling meaningful comparisons and a broader understanding of AI's effects. Ethical, legal, and human dimensions of AI use in pricing should also be addressed to ensure responsible adoption and stakeholder trust. Closing the gap between academic research and real-world practice is essential to transform AI's potential in hospitality into lasting business value.

Furthermore, experimental and mixed-method designs could be employed to test how guests and managers respond to algorithmic transparency and perceived fairness in pricing decisions. Particular attention should be given to small and independent hotels, where barriers to AI implementation remain substantial. Exploring "human-in-the-loop" frameworks could help balance automation with managerial judgment and oversight.

Finally, the development of explainable and interpretable AI models, those that can be audited, clearly communicated, and ethically assessed represents a key methodological direction for aligning technological progress with responsible RM practices. Future research could also empirically evaluate how such hybrid systems perform in real hotel environments, integrating contextual and behavioral data (e.g., booking time, number of guests, deposit type) into algorithms that remain under human supervision.

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