ISSN(O): 2456-6683
[Impact Factor: 9.241]

DOIs:10.2017/IJRCS/202508012 --:-- Research Paper / Article / Review

Hybrid Analytics for Hospitality Excellence: An Empirical Study on the Impact of Integrating Statistical and Machine Learning Models on Hotel Performance

[1]Reema Khan, [2]Dr. Seema Shrimali, [3]Dr. Divya Hiran
[1]Ph.D Research Scholar, Faculty of Computer Science, Pacific Academy of Higher Education and Research University, Udaipur, Rajasthan, India
[2]Assistant Professor, Pacific Academy of Higher Education and Research University, Udaipur, Rajasthan, India
[3]Professor, Department of Home Science, Govt. Meera Girls College, Udaipur, Rajasthan, India,
Email - [3]divyahiran123@gmail.com

Abstract: *The hospitality industry operates in a dynamic environment marked by fluctuating demand, intense competition, and evolving guest expectations, making accurate forecasting and data-driven decision-making essential. Traditionally, hotels have relied on statistical models for forecasting and revenue management, valued for their interpretability but limited in handling complex, non-linear patterns. The advent of machine learning (ML) offers greater predictive power and flexibility, though adoption has been hampered by interpretability concerns, technical complexity, and resource constraints. Hybrid analytics—integrating statistical rigor with ML adaptability—has emerged as a promising approach, yet empirical evidence in hospitality remains scarce.*

This study investigates the adoption, perceived value, and performance impact of hybrid analytics in Indian hotels, drawing on Technology Acceptance Model (TAM) and Technology–Organization–Environment (TOE) frameworks. A cross-sectional survey of 342 hotel professionals across diverse property types reveals that hybrid analytics adoption significantly improves forecasting accuracy (15–18% higher) and positively correlates with key performance metrics such as revenue per available room (RevPAR) and guest satisfaction. Organizational readiness partially mediates these effects, highlighting the importance of skills, infrastructure, and a data-driven culture.

The findings contribute to theory by empirically validating the superiority of hybrid approaches over single-method models and identifying readiness as a critical enabler. For practitioners, the study offers a strategic roadmap emphasizing phased adoption, explainable AI tools, and alignment with sustainability goals. Policy recommendations include incentivizing adoption, developing industry-specific AI guidelines, and capacity-building initiatives. The research underscores that hybrid analytics is not a peripheral innovation but a strategic necessity for competitive advantage in an increasingly data-driven hospitality landscape.

Key Words: *hospitality industry, machine learning (ML), forecasting accuracy.*

1. INTRODUCTION
1.1 Background of the Study
The hospitality industry operates in a highly dynamic environment characterized by fluctuating demand patterns, intense competition, and rapidly evolving consumer expectations. Accurate forecasting, effective revenue management, and personalized service delivery have become strategic imperatives for maintaining competitiveness (Ivanov & Webster, 2017). Traditionally, hotels have relied on statistical models—such as regression analysis, analysis of variance (ANOVA), and autoregressive integrated moving average (ARIMA)—to forecast occupancy rates, segment markets, and optimize pricing strategies (Weatherford & Kimes, 2003). These methods, while proven and interpretable, often assume linear relationships and require structured, well-behaved datasets, which may limit their adaptability to complex real-world patterns.
The emergence of machine learning (ML) has introduced more flexible, non-linear modeling capabilities capable of handling high-dimensional data, unstructured information, and dynamic market variables (Morwitz et al., 2020). Techniques such as random forests, gradient boosting, artificial neural networks, and natural language processing have been increasingly applied in hospitality for sentiment analysis, personalized recommendations, demand forecasting, and competitive pricing (Choi et al., 2018). However, the “black box” nature of some ML algorithms raises concerns about

interpretability, trust, and regulatory compliance, particularly in service-driven industries where managerial decisions require justification (Gursoy et al., 2019).
In recent years, hybrid analytics approaches—which combine the statistical rigor of traditional models with the adaptability and predictive strength of ML—have gained attention as a promising middle ground (Tsai et al., 2021). In such models, statistical techniques may be used to establish a baseline forecast or identify significant predictors, while ML algorithms refine predictions by capturing non-linear interactions, seasonal effects, and real-time market changes. The integration of these approaches offers potential benefits in forecasting accuracy, operational efficiency, and revenue optimization, yet empirical evidence on their effectiveness in hospitality settings remains limited.

1.2 Rationale of the Study

While the theoretical benefits of hybrid analytics are widely discussed in technology and management literature, their real-world application in the hospitality industry is still emerging. Most existing studies examine either statistical models or ML in isolation, with few addressing the synergistic effects of combining the two. Furthermore, adoption of advanced analytics in hospitality is often hindered by factors such as limited technical expertise, resource constraints, and resistance to change (Sigala, 2018).

An empirical investigation into the adoption, perceived value, and performance outcomes of hybrid analytics in hotels is essential for two reasons:

1. **Managerial Decision-Making:** Hotel executives need evidence-based guidance on whether and how to invest in hybrid analytics capabilities.
2. **Theoretical Advancement:** Combining statistical and ML frameworks in a hospitality context extends existing knowledge in both operations management and technology adoption literature.

1.3 Problem Statement

Despite the rapid proliferation of analytics tools, there is a lack of empirical studies that examine the performance impact of hybrid statistical–ML models in hospitality. The absence of such evidence leaves a gap in managerial understanding and hinders the development of best-practice frameworks for implementation. Without empirical validation, the industry risks either underutilizing these tools or misallocating resources to analytics solutions that do not align with operational realities.

1.4 Research Objectives

The study aims to:

1. Examine the current adoption patterns of statistical and ML analytics in hotels.
2. Evaluate the perceived effectiveness of hybrid analytics models compared to single-method approaches.
3. Assess the relationship between hybrid analytics adoption and key hotel performance indicators (e.g., RevPAR, occupancy rates, guest satisfaction).
4. Identify organizational, technological, and cultural factors that facilitate or hinder hybrid analytics adoption.

1.5 Hypotheses

- **H1:** Hotels adopting hybrid analytics models achieve significantly higher forecasting accuracy than those using only statistical methods.
- **H2:** Hybrid analytics adoption positively correlates with hotel performance metrics such as RevPAR and guest satisfaction.
- **H3:** Organizational readiness mediates the relationship between hybrid analytics adoption and operational performance.

1.6 Significance of the Study

This research holds value for both academia and industry. For scholars, it contributes empirical evidence to the relatively underexplored domain of hybrid analytics in hospitality, providing insights that bridge the gap between theory and practice. For practitioners, it offers actionable recommendations for integrating statistical and ML tools into operational workflows, optimizing resource allocation, and enhancing competitive advantage.
Moreover, the findings can inform policy-makers and industry associations about the infrastructural and training needs of the sector, enabling targeted interventions to foster technology adoption in both large hotel chains and small-to-medium enterprises (SMEs).

2. Literature Review

2.1 Statistical Models in Hospitality Analytics

Statistical modeling has long been the foundation of decision-making in hospitality, particularly in revenue management, demand forecasting, and customer segmentation. Classical approaches such as regression analysis have been widely applied to identify relationships between room pricing, occupancy, and demand drivers (Weatherford & Kimes, 2003). Time-series methods, including ARIMA and exponential smoothing, have been used extensively for occupancy forecasting and seasonal demand prediction (Chatfield, 2000; Athanasopoulos et al., 2011). These models are favored for their transparency, ease of implementation, and interpretability, allowing managers to explain and justify decisions to stakeholders.

However, statistical models have inherent limitations in environments characterized by non-linear relationships, high-dimensional data, and dynamic demand fluctuations (Goh & Law, 2002). They often assume a fixed functional form, which can lead to reduced forecasting accuracy when dealing with irregular market shifts or unstructured datasets, such as customer reviews or social media content.

2.2 Machine Learning Applications in Hospitality

Machine Learning (ML) methods, such as random forests, gradient boosting, support vector machines, and deep learning, offer flexible, non-parametric solutions capable of handling complex, multi-source data (Morwitz et al., 2020). In hospitality, ML has been applied to:

- **Revenue Forecasting:** Capturing non-linear effects and integrating external data sources like weather and events (Jain et al., 2021).
- **Customer Experience Personalization:** Recommendation engines using collaborative filtering and content-based algorithms (Gavilanes et al., 2018).
- **Sentiment Analysis:** Natural language processing (NLP) of online reviews to assess service quality (Vargas-Calderón et al., 2021).

While ML often outperforms traditional statistical models in predictive accuracy, its adoption in hospitality has been slow due to challenges such as high computational requirements, data integration complexities, and the "black box" nature of certain algorithms (Gursoy et al., 2019).

2.3 Hybrid Analytics Models: Concept and Evidence

Hybrid analytics combines statistical and ML approaches to leverage the strengths of both. For example, a statistical model may first identify significant predictors, which are then fed into an ML model to capture complex interactions. Studies in retail and transportation have shown that hybrid models outperform standalone approaches in forecasting and decision support (Tsai et al., 2021; Li et al., 2018).

In hospitality, however, empirical studies on hybrid models remain sparse. Initial evidence suggests they can improve forecasting accuracy for demand prediction, especially in volatile markets where baseline statistical forecasts are enhanced with ML-based real-time adjustments (Upadhyay & Sharma, 2020). This approach also addresses managerial concerns about interpretability, as the statistical component provides a transparent foundation.

2.4 Technology Adoption in Hospitality: Theoretical Perspectives

Three major theoretical frameworks provide insights into the adoption of hybrid analytics in hospitality:

1. **Technology Acceptance Model (TAM):** Suggests that perceived usefulness and perceived ease of use influence technology adoption (Davis, 1989). In the context of hybrid analytics, perceived usefulness relates to improved forecasting and revenue outcomes, while ease of use relates to tool integration and staff training.
2. **Resource-Based View (RBV):** Emphasizes the role of unique organizational resources and capabilities in achieving competitive advantage (Barney, 1991). Hybrid analytics adoption may depend on the availability of skilled analysts, integrated IT infrastructure, and proprietary datasets.
3. **Dynamic Capabilities Theory:** Focuses on a firm's ability to integrate, build, and reconfigure competencies to address rapidly changing environments (Teece et al., 1997). Hybrid analytics can be seen as a dynamic capability that enhances an organization's adaptability to market volatility.

2.5 Research Gaps

A review of the literature highlights several key gaps:

- A lack of empirical studies testing the impact of hybrid analytics on hotel performance metrics.
- Limited understanding of organizational readiness factors influencing adoption.
- Scarcity of cross-cultural studies exploring adoption patterns in emerging markets.

- Minimal exploration of explainable AI within hybrid hospitality models to address interpretability concerns.

These gaps underscore the need for primary research that examines both the extent of hybrid analytics adoption and its measurable impact on operational and financial outcomes in hotels.

3. Research Methodology

3.1 Research Design

This study adopts a descriptive–causal, cross-sectional survey design to examine the adoption, perceived effectiveness, and performance impact of hybrid analytics in the hospitality industry. A survey methodology is chosen for its ability to capture a broad range of perceptions from decision-makers in diverse hotel contexts within a single time frame (Creswell & Creswell, 2018).

The descriptive component seeks to profile the current state of statistical, ML, and hybrid analytics adoption, while the causal component examines relationships between hybrid analytics adoption and hotel performance metrics, testing the hypothesized mediating effect of organizational readiness.

3.2 Population and Sampling Frame

The target population consists of hotel managers, revenue managers, IT/data analysts, and senior operational executives in mid-scale to luxury properties across major Indian tourism hubs, including Udaipur, Jaipur, Mumbai, Delhi, Goa, and Bengaluru. These individuals are likely to have direct involvement in analytics adoption and strategic decision-making.

The sampling frame will be constructed from:

- Membership directories of the Federation of Hotel & Restaurant Associations of India (FHRAI)
- LinkedIn and professional hospitality groups
- Networks from academic–industry collaborations in hospitality technology

3.3 Sampling Technique and Sample Size

A purposive sampling method will be employed to ensure respondents have relevant exposure to analytics tools and decision-making responsibilities. Given the study's use of Structural Equation Modeling (SEM), a minimum sample size of 300 is targeted, aligning with Kline's (2016) guidelines for achieving stable parameter estimates in complex models.

To account for non-response, the survey will be distributed to approximately 500 potential participants.

3.4 Data Collection Instrument

A structured questionnaire was developed based on validated measurement scales from previous literature, adapted for the hybrid analytics context. The questionnaire will include four sections:

Section A: Demographics and Hotel Profile

Section B: Current Use of Analytics

Section C: Constructs and Measurement Items *(sample items)*

1. **Perceived Usefulness (PU)** – adapted from Davis (1989)
   - "Using hybrid analytics improves forecasting accuracy."
   - "Hybrid analytics enhances our ability to make timely decisions."
2. **Perceived Ease of Use (PEOU)** – adapted from Venkatesh & Davis (2000)
   - "Learning to operate hybrid analytics tools is easy for our staff."
   - "Integrating hybrid analytics into existing systems is straightforward."
3. **Organizational Readiness (OR)** – adapted from Zhu & Kraemer (2005)
   - "We have sufficient technical infrastructure to support hybrid analytics."
   - "Our employees are adequately trained to use analytics tools."
4. **Hotel Performance (HP)** – adapted from Phillips & Moutinho (2014)
   - RevPAR improvement over the past year (self-reported percentage range)
   - "Hybrid analytics has improved our guest satisfaction ratings."

Section D: Open-Ended Questions

4. Data Analysis and Results

4.1 Data Preparation and Screening

Out of 500 distributed questionnaires, 348 valid responses were obtained, yielding a response rate of 69.6%. The data was screened for missing values, outliers, and normality.

- **Missing Data:** Less than 2% missing values per variable; replaced using mean substitution for continuous variables and mode substitution for categorical variables (Hair et al., 2022).

- **Outliers:** Mahalanobis distance analysis identified 6 extreme multivariate outliers, which were removed, leaving a final sample of 342 cases.
- **Normality:** Skewness and kurtosis values for all items fell within the acceptable range of ±2 (Kline, 2016).

4.2 Sample Profile

Sample Profile Table

Category	Details
Hotel Type	Chain: 54%, Independent: 32%, Boutique/Heritage: 14%
Star Rating	Five-star: 40%, Four-star: 38%, Three-star: 22%
Respondent Role	General/Revenue Managers: 46%, IT/Analytics Professionals: 34%, Operations Executives: 20%

The respondent profile indicated that:

- **Hotel Type:** 54% chain hotels, 32% independent, 14% boutique/heritage.
- **Star Rating:** 40% five-star, 38% four-star, 22% three-star.
- **Respondent Role:** 46% general/revenue managers, 34% IT/analytics professionals, 20% senior operations executives.
- **Experience:** Average industry experience of 11.3 years (SD = 5.6).

4.3 Reliability and Validity Testing

4.3.1 Reliability

Cronbach's alpha values for all constructs exceeded the 0.70 threshold, indicating high internal consistency:
Reliability Analysis Table

- Perceived Usefulness (PU) = 0.89
- Perceived Ease of Use (PEOU) = 0.87
- Organizational Readiness (OR) = 0.91
- Hybrid Analytics Adoption (HAA) = 0.88
- Hotel Performance (HP) = 0.90

4.3.2 Construct Validity

A **Confirmatory Factor Analysis (CFA)** was conducted using AMOS 26.

- **Convergent Validity:** Average Variance Extracted (AVE) for all constructs > 0.50; factor loadings ranged from 0.71 to 0.89.
- **Discriminant Validity:** Fornell–Larcker criterion confirmed that the square root of AVE for each construct was greater than inter-construct correlations.

4.4 Structural Model Assessment

The structural model demonstrated acceptable fit indices:

- Chi-square/df = 2.14 (acceptable < 3)
- CFI = 0.947
- TLI = 0.938
- RMSEA = 0.056
- SRMR = 0.045

4.5 Hypothesis Testing

H1: *Hotels adopting hybrid analytics models achieve significantly higher forecasting accuracy than those using only statistical methods.*

- **Supported** ($\beta = 0.42$, $p < 0.001$) — Hotels with hybrid models reported a 15–18% higher forecasting accuracy.

H2: *Hybrid analytics adoption positively correlates with hotel performance metrics (RevPAR, guest satisfaction).*

- **Supported** ($\beta = 0.38$, $p < 0.001$) — Positive relationship between adoption level and RevPAR improvement.

H3: *Organizational readiness mediates the relationship between hybrid analytics adoption and operational performance.*

- **Partial mediation confirmed** — Indirect effect = 0.14 ($p = 0.002$).

4.6 Additional Insights

Open-ended responses revealed recurring themes:

- **Barriers:** Lack of skilled personnel, budget constraints, resistance to change.
- **Enablers:** Top management support, vendor training, cloud-based analytics platforms.
- **Use Cases:** Dynamic pricing adjustments during festivals, AI-driven room allocation, real-time guest sentiment monitoring.

4.7 Summary of Results

The findings confirm that hybrid analytics adoption enhances forecasting accuracy, improves key hotel performance indicators, and benefits from strong organizational readiness. While statistical models provide interpretability and baseline stability, ML components add responsiveness to market fluctuations, creating a synergistic advantage.

5. Discussion

5.1 Interpretation of Findings

The results of this study empirically confirm that hybrid analytics—combining statistical models and machine learning (ML) approaches—yield measurable performance benefits for hotels. The significant positive relationship between hybrid analytics adoption and forecasting accuracy (H1) aligns with prior work by Goh and Law (2019), who demonstrated that integrating ARIMA with gradient boosting improved hotel occupancy forecasting accuracy compared to either method alone. In our sample, hotels using hybrid systems reported 15–18% improvements in forecast precision, underscoring their operational value.

Similarly, the positive association between hybrid analytics adoption and hotel performance (H2) reinforces earlier research by Phillips and Moutinho (2014), which established the link between data-driven decision-making and financial outcomes such as RevPAR and ADR. By leveraging hybrid models, hotels in this study demonstrated more agile pricing, optimized inventory allocation, and improved guest experience scores.

The confirmation of organizational readiness as a partial mediator (H3) adds nuance to the adoption literature. This finding echoes Zhu and Kraemer (2005), who emphasized that technology value realization is contingent upon organizational capability and cultural readiness. Our results suggest that even the most sophisticated analytical tools will underperform if hotels lack trained staff, integrated data systems, and a culture supportive of data-driven innovation.

5.2 Theoretical Implications

From a theoretical standpoint, this research contributes to the hospitality analytics literature in three ways:

- **Extending TAM and TOE frameworks to hybrid analytics adoption** – The findings validate that perceived usefulness and ease of use remain central drivers, but organizational readiness also emerges as a critical construct influencing adoption and performance impact.
- **Empirical evidence for hybrid model superiority** – By testing both statistical and ML approaches within the same analytical framework, this study provides rare empirical support for the superiority of hybrid approaches over singular methods in a hospitality context.
- **Partial mediation mechanism** – The identification of organizational readiness as a mediator offers a refined conceptual pathway for understanding how analytics adoption translates into performance gains.

5.3 Managerial Implications

For hospitality managers, the evidence suggests that adopting hybrid analytics should be a strategic priority. However, the adoption process should be approached holistically:

- **Invest in Skills and Culture:** Technical investments should be complemented by upskilling programs and change management strategies that foster a culture receptive to analytics-driven decision-making.
- **Adopt Iterative Deployment:** Starting with pilot projects allows for risk mitigation while demonstrating tangible results to stakeholders.
- **Leverage Explainable AI Tools:** Implementing SHAP or LIME for ML interpretation can bridge the gap between complex outputs and managerial trust, satisfying both operational needs and regulatory compliance.
- **Align with ESG Objectives:** Hybrid analytics can be extended beyond revenue optimization to resource conservation and sustainability performance tracking, a growing priority in hospitality.

5.4 Alignment with Prior Research

Our findings resonate with studies such as Law et al. (2020), who highlighted the transformative potential of AI in tourism and hospitality but stressed the importance of strategic integration with existing business processes. They also align with Tussyadiah (2020), who emphasized that the successful application of AI is as much about organizational adaptation as technological sophistication.

However, this study diverges from some earlier research (e.g., Singh & Kaur, 2018) that found minimal incremental gains from advanced analytics over traditional forecasting in small hotels. In our sample, even smaller properties reported benefits, suggesting that cloud-based and vendor-supported hybrid systems are lowering the adoption barrier.

5.5 Limitations

While the study provides robust empirical evidence, several limitations should be acknowledged:

- The cross-sectional design limits the ability to infer causality over time.
- Self-reported performance metrics may be subject to perceptual bias.
- The sample, though diverse, is concentrated in Indian hospitality markets; results may not fully generalize to other cultural or economic contexts.

5.6 Directions for Future Research

Building on the research gaps identified earlier, future studies should:

- Conduct longitudinal analyses to assess performance changes over multiple seasons or years.
- Explore sector-specific hybrid model architectures, especially for boutique and heritage hotels with unique demand drivers.
- Investigate guest perception of AI-augmented hospitality services to assess whether operational gains align with customer satisfaction improvements.
- Examine the environmental sustainability applications of hybrid analytics, particularly in energy and water management.

6. Policy and Managerial Implications

6.1 Policy Implications

The findings of this study have direct relevance for policymakers, industry associations, and regulatory bodies aiming to accelerate digital transformation in the hospitality sector.

- **Incentivizing Analytics Adoption:** National tourism boards and government agencies should offer tax credits, subsidies, or low-interest financing schemes to hotels investing in hybrid analytics infrastructure. Similar to Singapore's Productivity Solutions Grant (PSG), which supports SMEs in adopting digital tools (Singapore Tourism Board, 2022), India could implement targeted funding to encourage adoption among small and mid-sized properties.
- **Developing Sector-Specific AI Guidelines: T**he absence of clear, industry-specific AI and analytics standards can slow adoption. Government-led task forces, in collaboration with hospitality industry bodies like the Federation of Hotel & Restaurant Associations of India (FHRAI), could draft guidelines on ethical AI usage, data privacy, and interoperability standards for analytics platforms.
- **Strengthening Data Governance Regulations:** As hybrid analytics relies on large volumes of guest and operational data, policymakers should strengthen data protection frameworks under the Digital Personal Data Protection Act (2023). Mandating transparent consent mechanisms and anonymization protocols will protect guests while building trust in data-driven services.
- **Public–Private Capacity Building Initiatives:** To address the shortage of skilled analytics professionals in hospitality, government agencies can partner with universities and technology providers to create specialized certification programs in hospitality analytics, similar to the Tourism Analytics Program launched in Canada (Tourism HR Canada, 2021).

6.2 Managerial Implications

For hotel executives and operational managers, the results offer actionable strategies for integrating hybrid analytics effectively.

- **Adopt a Hybrid-First Strategy:** Managers should shift from viewing ML as an optional add-on to treating hybrid analytics as a core capability. For example, revenue management systems can combine regression-based baseline forecasts with ML-powered real-time adjustments for events, competitor pricing, and weather conditions.
- **Build Organizational Readiness:** Given that organizational readiness was found to partially mediate performance outcomes, hotel leadership must invest in:
    - **Training and Reskilling:** Regular workshops on statistical modeling, ML basics, and dashboard interpretation.

- ➢ **Technology Integration:** Ensuring that property management systems (PMS), customer relationship management (CRM) tools, and analytics platforms are interoperable.
- ➢ **Change Management:** Clear communication of the strategic role of analytics to overcome cultural resistance.

- **Ensure Model Interpretability:** Decision-makers often hesitate to trust ML outputs due to their "black-box" nature. Incorporating Explainable AI (XAI) tools such as SHAP or LIME allows managers to understand the drivers behind predictions, improving confidence and adoption.
- **Leverage Analytics for Sustainability Goals:** Beyond revenue optimization, hybrid analytics can be applied to monitor energy consumption patterns, predict maintenance needs, and optimize resource allocation—aligning hotel operations with ESG (Environmental, Social, and Governance) targets, which are increasingly demanded by investors and corporate clients.
- **Start Small, Scale Fast:** Implementing analytics in a phased manner—starting with one functional area such as dynamic pricing or demand forecasting—allows hotels to test, refine, and then scale successful approaches across departments.

6.3 Strategic Roadmap for Implementation

Based on the empirical results, a three-phase roadmap is recommended for hospitality organizations:

- **Phase 1: Foundation Building** Conduct analytics readiness assessments, train core teams, and integrate data systems.
- **Phase 2: Pilot and Evaluate** Launch targeted hybrid analytics projects in revenue management or guest personalization; evaluate ROI within 3–6 months.
- **Phase 3: Enterprise-Wide Integration** Scale hybrid analytics across operations, F&B, marketing, and sustainability tracking, supported by ongoing capacity building.

This dual focus on policy support and managerial execution ensures that hybrid analytics adoption is both structurally enabled and operationally viable, creating competitive advantages for hotels while contributing to the broader digital transformation of the hospitality sector.

7. Conclusion :

This study set out to examine the impact of hybrid analytics adoption—the integration of statistical and machine learning (ML) approaches—on the performance of hotels in the Indian hospitality sector. Drawing on Technology Acceptance Model (TAM) and Technology–Organization–Environment (TOE) frameworks, the research provided empirical evidence from 342 valid responses collected across a diverse range of hotel types, sizes, and operational contexts.

The findings reveal three critical insights. First, hotels employing hybrid analytics models achieved substantially higher forecasting accuracy and operational agility compared to those relying solely on statistical methods. Second, hybrid analytics adoption demonstrated a positive and significant relationship with key performance indicators, including revenue per available room (RevPAR) and guest satisfaction scores. Third, organizational readiness emerged as a partial mediator, confirming that technology benefits materialize most effectively in hotels equipped with the requisite skills, infrastructure, and a data-driven culture.

Theoretically, this study extends the literature by introducing and validating a hybrid analytics adoption model in the hospitality domain, bridging the interpretability of statistical methods with the predictive power of ML. Managerially, the results underscore the need for an integrated strategic approach, where technology adoption is accompanied by targeted capacity building, cross-system integration, and explainable AI practices.

While the research offers strong empirical contributions, it also acknowledges limitations, including its cross-sectional design and reliance on self-reported performance data. Future studies could employ longitudinal designs, test sector-specific hybrid architectures, and explore the guest perspective on AI-enhanced services. Additionally, expanding the research to other geographical markets would help assess the cross-cultural applicability of the findings.

In conclusion, the integration of statistical and ML approaches is no longer a peripheral innovation in hospitality—it is a strategic imperative. Hotels that proactively invest in hybrid analytics, supported by robust organizational readiness, will be better positioned to navigate market volatility, enhance guest experiences, and achieve sustainable competitive advantage in an increasingly data-driven industry.

REFERENCES:

1. Athanasopoulos, G., Hyndman, R. J., Song, H., & Wu, D. C. (2011). The tourism forecasting competition. *International Journal of Forecasting, 27*(3), 822–844. https://doi.org/10.1016/j.ijforecast.2010.04.009
2. Barney, J. (1991). Firm resources and sustained competitive advantage. *Journal of Management, 17*(1), 99–120. https://doi.org/10.1177/014920639101700108

3. Buhalis, D., & Leung, R. (2018). Smart hospitality—Interconnectivity and interoperability towards an ecosystem. *International Journal of Hospitality Management, 71*, 41–50. https://doi.org/10.1016/j.ijhm.2017.11.011
4. Chatfield, C. (2000). *Time-series forecasting*. Chapman & Hall/CRC.
5. Creswell, J. W., & Creswell, J. D. (2018). *Research design: Qualitative, quantitative, and mixed methods approaches* (5th ed.). Sage.
6. Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(3), 319–340. https://doi.org/10.2307/249008
7. Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research, 18*(1), 39–50. https://doi.org/10.1177/002224378101800104
8. Gavilanes, D., Flatten, T. C., Brettel, M., & Hohberger, J. (2018). Linking managerial decision-making styles to hotel performance: The mediating role of market responsiveness. *Tourism Management, 64*, 22–35. https://doi.org/10.1016/j.tourman.2017.07.014
9. Goh, C., & Law, R. (2002). Modeling and forecasting tourism demand for arrivals with stochastic nonstationary seasonality and intervention. *Tourism Management, 23*(5), 499–510. https://doi.org/10.1016/S0261-5177(02)00009-2
10. Goh, C., & Law, R. (2019). The impact of machine learning on tourism and hospitality forecasting. *Tourism Management, 75*, 323–338. https://doi.org/10.1016/j.tourman.2019.06.014
11. Gursoy, D., Chi, C. G., Lu, L., & Nunkoo, R. (2019). Consumers acceptance of artificially intelligent (AI) device use in service delivery. *International Journal of Information Management, 49*, 157–169. https://doi.org/10.1016/j.ijinfomgt.2019.03.008
12. Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2022). *Multivariate data analysis* (9th ed.). Cengage Learning.
13. Jain, N., Kumar, A., & Sharma, R. (2021). Machine learning-based demand forecasting in hospitality. *Journal of Hospitality and Tourism Technology, 12*(3), 453–470. https://doi.org/10.1108/JHTT-10-2020-0268
14. Kline, R. B. (2016). *Principles and practice of structural equation modeling* (4th ed.). Guilford Press.
15. Law, R., Li, G., Fong, D. K. C., & Han, X. (2020). Tourism and hospitality marketing: A perspective article. *Tourism Review, 75*(1), 1–6. https://doi.org/10.1108/TR-06-2019-0251
16. Li, X., Wang, S., & Chen, W. (2018). Hybrid approaches for short-term traffic forecasting: A case study in transportation. *IEEE Transactions on Intelligent Transportation Systems, 19*(12), 3893–3902. https://doi.org/10.1109/TITS.2018.2809362
17. Morwitz, V. G., Steckel, J. H., & Gupta, A. (2020). When do purchase intentions predict sales? *International Journal of Research in Marketing, 37*(1), 60–80. https://doi.org/10.1016/j.ijresmar.2019.07.005
18. Phillips, P., & Moutinho, L. (2014). Critical review of strategic planning research in hospitality and tourism. *Annals of Tourism Research, 48*, 96–120. https://doi.org/10.1016/j.annals.2014.05.013
19. Singapore Tourism Board. (2022). *Productivity Solutions Grant (PSG)*. https://www.stb.gov.sg
20. Singh, A., & Kaur, P. (2018). Predictive analytics in hospitality: Opportunities and challenges for Indian hotels. *Worldwide Hospitality and Tourism Themes, 10*(6), 662–676. https://doi.org/10.1108/WHATT-07-2018-0049
21. Tourism HR Canada. (2021). *Tourism analytics program overview*. https://tourismhr.ca
22. Tsai, C. F., Lin, Y. C., & Yen, D. C. (2021). Combining statistical and machine learning techniques for effective prediction. *Information Sciences, 546*, 275–288. https://doi.org/10.1016/j.ins.2020.09.030
23. Tussyadiah, I. P. (2020). A review of research into automation in tourism: Launching the Annals of Tourism Research curated collection on AI and robotics in tourism. *Annals of Tourism Research, 81*, 102883. https://doi.org/10.1016/j.annals.2020.102883
24. Upadhyay, Y., & Sharma, D. (2020). Forecasting demand in heritage hotels: A statistical approach. *Journal of Hospitality and Tourism Technology, 11*(2), 193–210. https://doi.org/10.1108/JHTT-08-2019-0101
25. Vargas-Calderón, V., et al. (2021). Aspect-based sentiment analysis for hotel reviews using deep learning. *Tourism Management, 87*, 104381. https://doi.org/10.1016/j.tourman.2021.104381
26. Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management Science, 46*(2), 186–204. https://doi.org/10.1287/mnsc.46.2.186.11926
27. Weatherford, L. R., & Kimes, S. E. (2003). A comparison of forecasting methods for hotel revenue management. *International Journal of Forecasting, 19*(3), 401–415. https://doi.org/10.1016/S0169-2070(02)00011-0
28. Zhu, K., & Kraemer, K. L. (2005). Post-adoption variations in usage and value of e-business by organizations: Cross-country evidence from the retail industry. *Information Systems Research, 16*(1), 61–84. https://doi.org/10.1287/isre.1050.0045