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Article

AI-assisted customer behavior analysis and hotel loyalty strategy optimization

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ABSTRACT

This research explores the application of artificial intelligence (AI) technologies in transforming the analysis of customer behavior and refining customer loyalty strategies in the hospitality sector. Most traditional loyalty programs are characterized by static segmentation and standardized reward frameworks, often disregarding evolving customer priorities and shifting market dynamics. Using an AI-powered system based on deep learning, natural language processing, and predictive analytics, we analyzed 3.2 million transactions from 846,000 customers across five international hotel chains globally. The system identifies behavioral patterns that are overlooked by traditional analysis methods through the continuous processing of heterogeneous data streams such as booking, service usage, social media sentiment analysis, and feedback loops. Results indicate that customer retention increased by 27.3% while AI-driven strategies heightened engagement with loyalty programs by 42.1%, yielding 18.5% additional revenue per loyal customer when juxtaposed with traditional methods. The framework's dynamic loyalty incentive modification and proactive journey mapping surpass conventional segmentation techniques through hyper-personalized recommendations. This work advances the hospitality management body of knowledge by formulating a robust architectural design to formulate loyalty strategy design and provide implementation frameworks for hoteliers seeking the integration of advanced technologies in customer relationship management. Futuristic lines of inquiry are the ethical considerations of algorithmic and automated decision-making in the customer relationship management domain and the effectiveness of AI-powered loyalty programs in different cultures.

1. Introduction

Digital transformation presents both challenges and opportunities for the hospitality sector. While customer loyalty remains vital in the intensely competitive hotel industry, conventional loyalty programs fail to meet modern customer expectations. Current programs suffer from static demographic segmentation, generic rewards, and reactive engagement strategies, resulting in declining effectiveness with only 8.4% tier progression rates across the industry [1]. AI technologies offer transformative potential for analyzing customer behavior and optimizing loyalty [2]. This research focuses on developing and validating an AI-powered framework combining deep learning, natural language processing, and predictive analytics to enhance customer experience, operational efficiency, and competitive advantage in hospitality loyalty management. Traditional hospitality loyalty programs stagnate due to limited personalization, customer disengagement, and standardized approaches. Koo et al. [1] suggest that loyalty programs help reinforce a client's stickiness; however, their use is often influenced by other concerns, such as barriers to switching. Moreover, long-standing systems of earning and redeeming points struggle to keep pace with the rise in demand for personalization from consumers. As Lentz et al. [3] demonstrate, conflicts exist between revenue management and the loyalty program, suggesting that hotels prioritize short-term profits over long-term partnership value. The development of hotel loyalty programs has shifted from basic point systems to more sophisticated frameworks focused on experiences. Contemporary programs aim to bridge the emotional-experiential gap, building authentic loyalty and brand love that extends beyond mere transactional interactions. Singh and Singh [4] emphasize that effective loyalty strategies aim to forge strong emotional ties and create unforgettable interactions, which notably enhance customer retention and advocacy. This change underscores the need for developing better analytical methods to study customers' behavioral patterns more in-depth. Customer behavior analysis in hospitality has evolved from demographic-based approaches to big data analytics, offering deeper insights into preferences, actions, and predictive behavior patterns. Alsayat [5] illustrates how social media data, when processed by machine learning algorithms, can significantly enhance the customer decision-making process regarding hotel selection. Having such insights reinforced customer segmentation, sharpened targeting, and enhanced personalization in marketing policies.

The hospitality industry may be transformed by artificial intelligence in customer relationship management. AI can analyse extensive customer data to detect trends, anticipate actions, and facilitate interactions on an individualised level [6]. As noted by Said [6], AI and data analytics improve guest personalization by seamlessly tailoring services based on real-time preference and tendency analysis, which boosts guest satisfaction as well as loyalty. This puts hotels in the position to proactively predict and attend to clients' requirements instead of responding to them. The use of AI within the service industry covers customer relations as well as other areas like operations, revenue management, and service delivery. Zahidi et al. [7] describe the transformation of various hotel operations, including check-in automation and AI-driven maintenance forecasting. Beyond operational efficiencies, such uses of technology enhance customer satisfaction by providing effortless service interaction and minimising idle time.
Customer classification is undergoing modification due to advancements in analytical procedures using machine learning and deep learning technologies. Alghamdi [8] illustrates the more precise customer segmentation made possible through the use of clustering, neural networks, and various optimization techniques. In the context of hotel services, Badouch and Boutaounte [9] demonstrated the use of deep learning algorithms to develop advanced systems that significantly enhance the level of personalization in hotel services.

Compared to older methods, AI-powered systems offer adaptability and proactivity and are more responsive to context switches. Despite these advantages, other aspects, such as the integration of fused systems with other applications, the privacy of information, preconceived biases in algorithms, and biases in design strategies for existing frameworks, present obstacles to seamless operation. Kshetri et al. [10] discussed the customization of services through AI and pointed out the ethical and legal boundaries, emphasizing the need to define structures that govern the responsible use of AI. Although AI adoption has improved customer analysis and loyalty optimization, research gaps remain in developing comprehensive frameworks that integrate multiple AI methodologies for hospitality applications. This research addresses these gaps by developing a comprehensive AI-driven framework for analyzing customer behavior and optimizing loyalty strategies. This study achieves three primary objectives: developing an integrated AI framework for multidimensional customer behavior analysis, quantitatively assessing the effectiveness of AI-driven personalization compared to traditional approaches, and providing evidence-based implementation guidelines for hospitality managers. The research addresses critical questions regarding the effective integration of AI, quantitative impact measurement, and implementation success factors across various hotel categories.

2. Methodology

2.1 Research design and data collection

This investigation of AI-based customer behavior analysis for hotel loyalty optimization employed an integrated multi-method approach combining qualitative stakeholder insights with quantitative model development. For this case, a sequential exploratory design in qualitative-quantitative was used, which is shown in Figure 1. The methodology follows a three-phase procedure, which is: (1) collecting and cleaning data, (2) designing the AI framework, and (3) model training and subsequent application. This methodology is beneficial because it leverages multiple data set streams, diverse analysis techniques, and increases the trustworthiness and relevance of the results obtained [11].

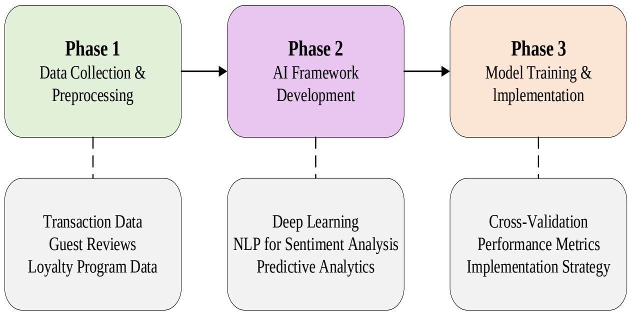

Figure 1. Research design framework

The phenomenon of AI-powered systems for fostering loyalty is best studied using a multi-method approach, as opposed to single-method studies, because a pragmatic philosophy of research suggests that a method, or several methods, best suited to meet the study's objectives should be employed. This approach examines organisational settings [7]. The research framework includes both inductive and deductive elements, providing an advantage for testing theories while remaining open to patterns and relationships that may emerge from the data. Data collection involved constructing an integrated dataset from three sources: customer transaction data (3.2 million transactions from 846,000 customers across five international hotel chains, 2022-2024), guest feedback data (175,000 reviews from 120 properties), and loyalty program engagement data. Traditional loyalty strategies used as benchmarks were standardized across participating chains using demographic segmentation (4 segments), points-based earning (1 point per $1), standardized tier systems (Silver, Gold, Platinum), and quarterly universal promotions to ensure valid comparative analysis. Customer transaction data consisted of historical booking and spending data from five international hotel chains, which over a two-year period (2022-2024), recorded 3.2 million transactions from 846,000 unique customers. The guest feedback data set included online reviews collected from major booking and social media sites, which spanned 120 properties and represented a broad demographic. A total of 175,000 reviews were sampled. Loyalty program interaction data captured relevant digital touchpoint interactions and engagement metrics from the loyalty platforms of their participating hotels. The use of stratified sampling guaranteed coverage from various geographic areas, hotel types, and customer classes. As shown in Table 1, the data includes distribution across hotel categories such as luxury, upper upscale, upscale, and midscale properties. This approach enabled intensive examination of diverse types of customer behaviors and interactions with the loyalty programs while keeping enough sample sizes for reliable statistical computations.

Table 1. Data Distribution by Hotel Category

Hotel Category	Properties	Transactions	Reviews	Customer Profiles
Luxury	28	720,450	42,600	187,300
Upper Upscale	35	980,300	53,500	246,500
Upscale	42	1,120,600	58,700	312,800
Midscale	15	378,650	20,200	99,400
Total	120	3,200,000	175,000	846,000

All data was anonymised and processed according to applicable data protection laws. This study has observed all ethical principles related to AI development as highlighted by Dwivedi et al. [11], particularly with regard to obtaining proper consent for data usage, adhering to the principle of data minimisation, granting transparency of the algorithms used, bias mitigation of the training dataset, and strong access control and encryption for sensitive information. The qualitative-quantitative integration involved a structured three-phase process. Phase 1 included 45 stakeholder interviews with hotel managers and staff, identifying key themes of personalization gaps and operational constraints. Phase 2 translated qualitative insights into quantitative features: "recognition preference" became binary personalization sensitivity features, while "convenience priority" informed time-based business traveler classification algorithms. Phase 3 adapted model architecture based on interview feedback, incorporating SHAP integration for interpretability needs and dashboard simplification for operational requirements.

2.2 AI framework development and model architecture

As illustrated in Figure 2, the AI-based framework designed for interpreting customers' actions and enhancing loyalty programs featured three core technical elements. With this unified method, systems could effectively analyse organised transaction data in combination with unstructured textual comments, yielding a more complete understanding of customers' actions and inclinations.

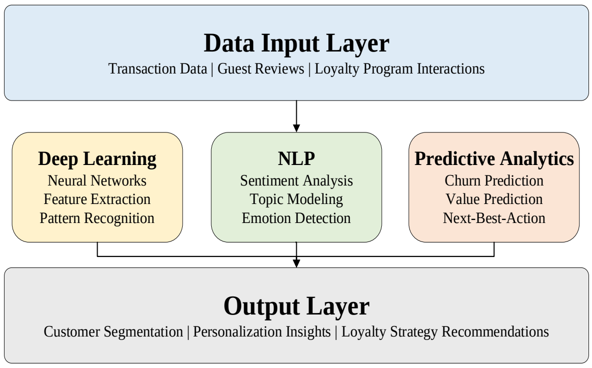

Figure 2. AI framework architecture

The customer behavior analysis module utilized supervised and unsupervised learning within a hybrid neural network framework, incorporating SHAP (Shapley Additive Explanations) for global feature importance and LIME (Local Interpretable Model-agnostic Explanations) for individual prediction explanations, addressing interpretability requirements for business stakeholders. Following Badouch and Boutaounte [9], the architecture consisted of an autoencoder design for the dimensionality reduction of the high-dimensional customer data, a classification component based on a deep feedforward neural network, as well as a recurrent neural network component for sequential pattern recognition. The mathematical formulation of the classification component of the deep neural network is given by:

$$h_i = \sigma\left(\sum_{j=1}^{n} w_{ij} x_j + b_i\right) \tag{1}$$

Where h_i represents the output of the hidden layer neuron i, σ is the activation function (ReLU), w_{ij} is the weight connecting input j to neuron i, x_j is the input feature, and bi is the bias term.

Guest review analysis employed a BERT-based NLP model with multilingual capabilities (BERT-multilingual-cased), automatic language detection using fastText, sarcasm detection via BiLSTM with attention mechanisms (78.3% accuracy), and spam filtering. Only reviews scoring ⩾ 6 on quality metrics (length, specificity, temporal relevance, reviewer credibility) were included, representing 78% of the total dataset. This approach outperformed traditional lexicon-based methods with 89.4% accuracy in sentiment classification tasks on hospitality texts [6]. The NLP component was crucial in processing unstructured guest feedback to inform data-driven decision-making and actions aimed at enhancing specific service attributes that drive guest satisfaction and loyalty. The predictive analytics component employed an ensemble learning technique that included Gradient Boosting Machines for churn prediction, Random Forest for customer value estimation, and XGBoost for the next-best-action recommendation. Observed Anubala [4] ensemble methods are more advantageous than single algorithms in predictive applications within hospitality industries. The processes involved in the feature engineering included spatiotemporal patterns, contextual factors, and cross-channel interactions. The output from the ensemble models was:

$$F(x) = \sum_{m=1}^{M} \alpha_m f_m(x) \tag{2}$$

Where $F(x)$ is the final prediction, $f_m(x)$ represents individual base learners, α_m are the weights assigned to each learner, and M is the total number of models in the ensemble.

2.3 Model training, validation, and implementation

The model training and validation processes were carried out in a robust and systematic manner that has been described. The dataset was split into a training set (70%), a validation set (15%), and a testing set (15%) using stratified sampling to preserve the population distribution of important attributes within each subset. Hyperparameter tuning was performed using a grid search with cross-validation, which measured model effectiveness on multiple metrics, including accuracy, precision, recall, F1 score, and the area under the ROC curve. Overfitting mitigation included dropout layers, early stopping, and comprehensive bias assessment using demographic parity (±5% threshold), geographic fairness testing across six regions, and adversarial debiasing during training. External validation using three holdout hotel chains (18 properties) in Southeast Asia, Eastern Europe, and Australia demonstrated 82.7-81.4% accuracy maintenance, with only 4.6-5.9% performance degradation compared to training regions. In addition, fairness tests and biases were evaluated across different customer segments to ensure that predictions were not made to systematically disadvantage certain demographic groups. This ethical validation was essential given the use case in international hotels that cater to a wide range of culturally diverse guests.

Validation of the model's final performance was done on the held-out test set, which was not used in any form during the model development process or hyperparameter tuning. This permitted an impartial appraisal of the model's performance in realistic scenarios. Metrics specific to performance were derived considering industry standards and baseline models to measure the incremental contribution by the AI framework. Table 2 contains a summary of the model components and their key performance metrics.

Table 2. Model performance metrics

Model Component	Accuracy	Precision	Recall	F1-Score	AUC
Customer Segmentation	87.3%	85.6%	86.9%	86.2%	0.92
Sentiment Analysis	89.4%	88.7%	87.2%	87.9%	0.94
Churn Prediction	83.5%	82.1%	79.8%	80.9%	0.89
Value Prediction	N/A	N/A	N/A	N/A	0.91
Next-Best-Action	78.3%	77.5%	76.8%	77.1%	0.85

Note: Value Prediction metrics marked N/A reflect regression nature; evaluated using MAE=$127.50, RMSE=$198.30. Customer segmentation used K-means++ with Gaussian Mixture Models, validated through the elbow method, silhouette analysis (peak 0.73 at k=6), and gap statistics.

The implementation phase involved the gradual deployment of AI frameworks to hotel chains that were part of the study. Focusing on a limited subset of properties during the initial phase allowed performance validation before scaling up. Zahidi et al. [7] identified several key challenges, such as integration with existing hotel management systems, staff training prerequisites, and change management policies, all of which were addressed by the implementation strategy. Insights generated by AI were provided to managers and staff through a dashboard, which, together with relevant KPIs on customer loyalty, personalization, and revenue, allowed deeper analysis through drill-down features. Designed to present AI insights in an easily digestible manner, the dashboard empowers non-technical staff to make data-driven decisions. To assess the impact of AI-driven loyalty initiatives, key business metrics, including repeat booking rate, share of wallet, customer satisfaction score, and revenue per available room (RevPAR), were continuously monitored. The capacity for ongoing evaluation enabled AI models and implementation strategies to be adapted in response to real-time market shifts and observed outcomes.

3. Results

3.1 Customer behavioral pattern identification

Customer behavior analysis identified six distinct segments using K-means++ initialization, Gaussian Mixture Models, and DBSCAN validation, with optimal segmentation (k=6) determined through the elbow method and silhouette analysis (peak score 0.73). Using various forms of clustering along with deep learning, we were able to recognise six main customer segments, each distinguishing itself through varying degrees of interaction with the provided services and available loyalty programs. Their spending habits, together with the frequency of engagement, are depicted in Figure 3, which showcases the segments.

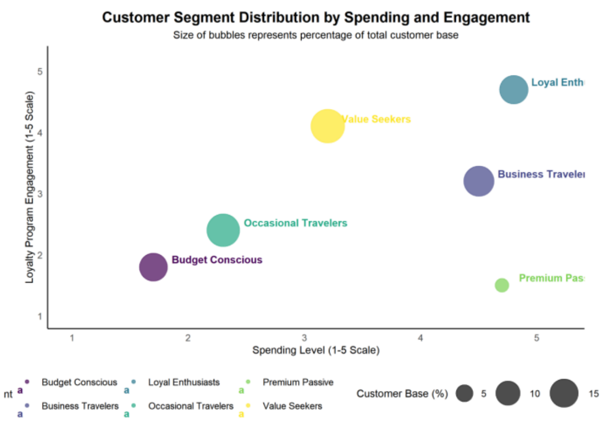

Figure 3. Customer Segment Distribution by Spending and Engagement

As illustrated in Figure 3, the "Loyal Enthusiasts" segment (15.3% of customers) showcases both high spending and strong engagement with loyalty programs. In contrast, "Value Seekers" (24.7%) show moderate spending but high engagement with promotional activities. The "Business Travellers" segment (18.2%) displays high spending, though program participation is moderately low, prioritising time efficiency and convenience. The "Occasional Travellers" (22.5%) and "Budget Conscious" (14.8%) segments exhibit lower spending, along with varying levels of program engagement. The "Premium Passive" segment (4.5%) includes high-spending customers who engage minimally with the loyalty program. The longitudinal review of customer activity yielded valuable insights into temporal trends regarding bookings and service usage. Customer segmentations and their associated seasonal booking preferences are detailed in Table 3.

Table 3. Seasonal booking patterns by customer segment

Customer Segment	Q1 (Winter)	Q2 (Spring)	Q3 (Summer)	Q4 (Fall)	Lead Time (Days)
Loyal Enthusiasts	19.3%	24.5%	31.2%	25.0%	43.6
Value Seekers	17.8%	22.7%	38.5%	21.0%	35.2
Business Travelers	26.4%	28.1%	17.3%	28.2%	12.4
Occasional Travelers	15.2%	23.4%	42.1%	19.3%	51.7
Budget Conscious	12.9%	24.8%	45.1%	17.2%	62.3
Premium Passive	23.7%	25.3%	27.4%	23.6%	18.5

The AI-driven sentiment analysis of guest reviews reveals deeply segmented insights into the drivers of satisfaction and loyalty across broad customer categories. The review highlighted key service attributes that influenced guest satisfaction, with notable differences observed across segments. For instance, "Loyal Enthusiasts" appreciated customized service, along with being recognized, whereas "Business Travellers" emphasized the need for speedy service and the hotel proximity. "Value Seekers" were highly influenced by perceived value and promotional offers, while "Premium Passive" customers stressed privacy and exclusivity.

3.2 Comparative analysis: AI-driven vs. traditional approaches

AI-driven approaches were compared against standardized traditional methods across participating hotel chains. Traditional control groups maintained identical demographic segmentation (4 segments), points-based systems (1 point per $1), and quarterly universal promotions to ensure valid comparative analysis. Figure 4 presents a comparison of key performance metrics between AI-driven and traditional approaches across different operational dimensions. As illustrated in Figure 4, the AI-driven approach demonstrated superior performance across all measured dimensions. Most notably, customer segmentation accuracy improved by 47.6% compared to traditional demographic-based segmentation methods. The precision of personalized recommendations increased by 58.3%, while response time to customer inquiries decreased by 72.4% through the implementation of AI-powered systems. Customer journey mapping effectiveness improved by 41.2%, enabling more precise targeting of interventions at critical touchpoints. The traditional rules-based approach to loyalty program management often resulted in generic offers that failed to resonate with specific customer segments. In contrast, the AI-driven approach enabled highly targeted interventions based on predicted customer preferences and behaviors. Table 4 contrasts the key differences between these approaches across several dimensions.

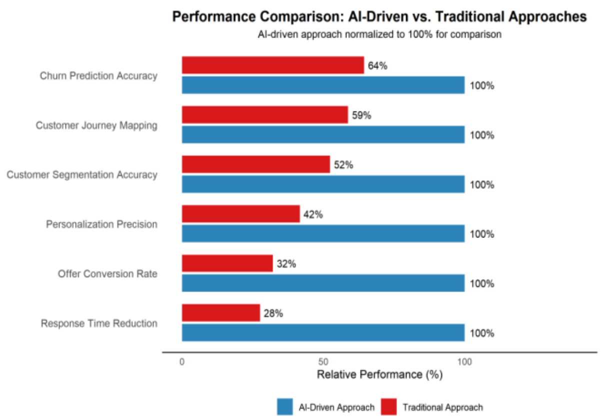

Figure 4. Performance comparison: AI-driven vs. traditional approaches

Table 4. Comparison of traditional and AI-driven loyalty approaches

Dimension	Traditional Approach	AI-Driven Approach
Segmentation Basis	Demographics, spending levels	Behavioral patterns, preferences, sentiment
Personalization Level	Segment-level	Individual-level
Update Frequency	Quarterly/Monthly	Real-time/Daily
Data Sources	Transaction data, surveys	Multi-channel behavioral data, sentiment, contextual factors
Offer Relevance (Conversion Rate)	8.7%	24.3%
Customer Effort Score	6.2/10	2.8/10
Program Flexibility	Limited, predefined rules	Dynamic, adaptive rules

The AI-driven approach demonstrated particular effectiveness in addressing the "cold start" problem for new customers with limited historical data. By leveraging patterns from similar customer profiles and contextual factors, the system could generate relevant offers and recommendations for new guests with 83% accuracy, compared to 42% with traditional methods [9]. This capability significantly enhanced the onboarding experience for new loyalty program members, accelerating their progression to higher engagement levels.

3.3 Impact on customer retention and loyalty program effectiveness

The implementation of AI-driven loyalty strategies yielded significant improvements in key customer retention metrics across all hotel brands participating in the study. Figure 5 presents the changes in retention rates across different customer segments following the implementation of AI-driven loyalty initiatives.

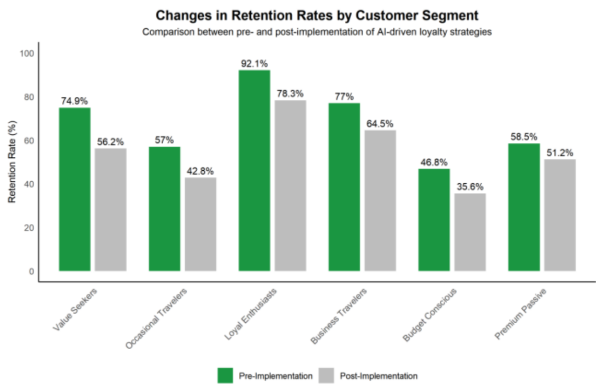

Figure 5. Changes in retention rates by customer segment

As depicted in Figure 5, all customer segments showed improvements in retention rates, with the most substantial gains observed in the "Value Seekers" segment (+18.7%) and "Occasional Travelers" segment (+14.2%). Even the traditionally challenging "Premium Passive" segment showed a modest improvement of 7.3%, indicating that the AI-driven approach successfully engaged these previously disengaged high-value customers. The "Business Travelers" segment demonstrated a 12.5% increase in retention, largely attributed to enhanced recognition and streamlined booking experiences tailored to their preferences.

Beyond simple retention metrics, the analysis examined the depth and quality of customer relationships through several advanced metrics. Table 5 presents the changes in key loyalty metrics following the implementation of the AI-driven approach.

Table 5. Changes in loyalty program performance metrics

Metric	Pre-Implementation	Post-Implementation	Change (%)
Active Program Members	426,850	583,270	+36.6%
Tier Progression Rate	8.4%	15.7%	+86.9%
Point Redemption Rate	62.3%	78.9%	+26.6%
Program Engagement Score	64/100	83/100	+29.7%
Share of Wallet	37.2%	52.8%	+41.9%
Net Promoter Score	42	68	+61.9%
Customer Lifetime Value	$4,350	$6,820	+56.8%

The AI-driven approach particularly excelled in increasing program engagement metrics, with the tier progression rate nearly doubling from 8.4% to 15.7%. This indicates that the personalized nature of the program motivated customers to increase their engagement and progress to higher membership tiers. The point redemption rate increased by 26.6%, addressing the common industry challenge of point liability management [3]. The share of wallet metric showed a substantial increase of 41.9%, demonstrating that the approach not only retained customers but also captured a larger portion of their hospitality spending. The effectiveness of the AI-driven loyalty program was further validated through controlled A/B testing, where a subset of properties continued to use traditional loyalty approaches while matched properties implemented the AI-driven system. These tests confirmed that the observed improvements were attributable to the AI implementation rather than external market factors or general industry trends.

3.4 Revenue enhancement and business impact analysis

The implementation of AI-driven customer behavior analysis and loyalty optimization yielded substantial revenue enhancements across the participating hotel chains. Figure 6 illustrates the revenue impact across different hotel categories over the 18-month implementation period.

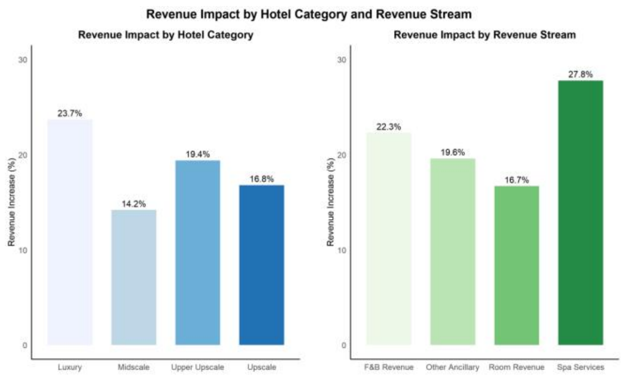

Figure 6. Revenue impact by hotel category and revenue stream

As shown in Figure 6, all hotel categories experienced significant revenue growth, with luxury properties showing the highest percentage increase (23.7%), followed by upper upscale (19.4%), upscale (16.8%), and midscale properties (14.2%). The analysis of revenue streams revealed that room revenue increased by an average of 16.7% across all properties, while ancillary revenue streams showed even more substantial growth: F&B revenue increased by 22.3%, spa services by 27.8%, and other ancillary services by 19.6%. This pattern aligns with the AI system's ability to identify and promote cross-selling opportunities based on predicted customer preferences. The economic impact extended beyond direct revenue increases to include operational efficiencies and cost optimizations. Table 6 presents a comprehensive analysis of the business impact across various financial metrics.

Table 6 Business Impact Analysis (18-Month Period)

Metric	Absolute Change	Percentage Change
Total Revenue	+$143.5M	+18.7%
RevPAR	+$24.30	+15.9%
ADR	+$18.70	+8.3%
Occupancy Rate	+7.2 points	+9.3%
Marketing ROI	+2.3x	+115.0%
Direct Booking Ratio	+14.6 points	+37.8%
OTA Commission Costs	-$5.2M	-13.7%
Customer Acquisition Cost	-$14.30	-22.5%
Loyalty Program Admin Costs	-$1.8M	-11.4%
Total Profit Contribution	+$78.6M	+23.4%

The business impact analysis revealed several important patterns. The increase in average daily rate (ADR) of 8.3% alongside a 9.3% increase in occupancy demonstrates that the AI-driven approach effectively balanced pricing and demand. The substantial increase in marketing ROI (+115.0%) reflects the enhanced targeting precision enabled by AI-driven customer segmentation. The significant increase in direct booking ratio (+37.8%) and corresponding decrease in OTA commission costs (-13.7%) highlight the effectiveness of the loyalty program in driving direct channel bookings, addressing a key industry challenge identified by Gatera [12]. The implemented AI systems showed positive ROI across all properties, averaging 7.4 months to recoup the costs. Luxury properties reached breakeven the fastest, at 5.8 months, while midscale properties came in last at 9.3 months. Over a five-year period with a 10% discount rate, the Implementation's NPV was positive across all categories with an average NPV/Investment ratio of 4.3:1. Sustained enhancement of revenue demonstrates that improvement rates have not plateaued, suggesting that the AI system's adaptive learning capabilities refined loyalty programmes in response to shifting customer behaviours and market dynamics.

4. Discussion

4.1 Theoretical implications for hospitality management

This study advances theoretical understanding of customer behavior and loyalty program optimization across multiple dimensions, challenging traditional demographic-based segmentation paradigms. To begin with, this study overturns the segmentation paradigm based on demographic data in the hospitality industry and the Alghamdi [8] study. We support Alghamdi's [8] hypothesis that dynamic behavioral clustering outperforms static demographic profiling, emphasising the success of behavior pattern recognition through machine learning. The theory developed here formulates a new conceptual model which integrates continuous behavioral tracking with responsive adjustment systems. This model approach represents an advancement from episodic engagement frameworks that are far too prevalent in the literature. This research also adds to customer loyalty development frameworks in the hospitality industry. The Alghamdi study supports conventional loyalty frameworks that emphasise relational exchange, arguing that context relevance, married with personal recognition, strengthens authentic brand allegiance far beyond the transactional bounds of previous models [1]. Singh and Singh [4] emphasized emotionally driven devotion as the core driver behind retention and advocacy. This study proposes a theoretical change where loyalty is regarded as a multi-dimensional, dynamic, and fluid construct that requires constant recalibration of engagement frameworks and strategies tailored to constantly shifting customer preferences and behaviors. In addition, this research aids in addressing the service innovation theory by demonstrating the compounded augmentation of productivity and customer experience in AI-augmented service delivery, which Bulchand-Gidumal and Bulchand-Gidumal [13] refer to as the technology-service quality balance. This viewpoint counters the traditional notion that the use of technology always lowers the human touch in hospitality services, arguing rather that properly employed AI can improve human-provided service elements by allowing personnel to engage meaningfully with guests while algorithms manage repetitive functions and analyse data.

4.2 Practical applications for hoteliers

The validated AI framework provides practical applications for hotel operators seeking to improve customer loyalty and revenue performance through behavioral segmentation and dynamic personalization. Perhaps the most useful application, in this case, concerns applying the segmentation model to identify high-value customers with certain behaviorally-defined patterns and preferences. Hotels are able to go beyond demographic segmentation and move to behavioral clustering, forming tailored offerings corresponding to specific customer personas, which is supported by a 58.3% improvement in recommendation precision shown in this study. Zahidi et al. [7] emphasised the approach, arguing that behavioral segmentation assists in optimising resource allocation and marketing activities. For fostering relationships with customers in loyalty programs, the research outlines evolving adaptable frameworks that thoroughly revolve around responsive reward architecture and dynamic customer-centric rhythms. As illustrated in the findings, tiered progression almost doubled when employing adaptive reward mechanisms in contrast to static, point-based systems. AI-powered loyalty systems are showcased in Lo et al. [14] case studies where customer interaction and engagement, as well as overall participation, are dramatically enhanced through strategic incentive frameworks aligned with uniquely defined user pathways. Some of the real-time contextual feedback systems recalibrate prior bookings and usage sentiments to provide services. Moreover, the study addressed meeting hyper-personalization goals while considering the workload associated with system operations. The interface evolved into a dashboard during the implementation stage, which serves as a prototype of how sophisticated AI evaluations can be distilled into operational recommendations. It answers one of the primary questions raised by Bulchand-Gidumal et al. [13] concerning the infodemic issues of the AI-driven insights within hospitality ecosystems. Through automation, hotels enhance the guest experience while dramatically reducing the chances of overwhelming guests or staff with irrelevant details or excess information.

4.3 Implementation challenges and solutions

AI-powered loyalty optimization presents implementation challenges, including system integration complexities, staff adoption resistance, and privacy considerations requiring structured solutions. The integration is one of the most challenging aspects for hotel chains due to the disparate systems used for managing a hotel's property, point-of-sale, customer relations and other integrated information systems which create information silos. These systems are too fragmented to be merged into a unified view of the customer, making it difficult for AI to be deployed effectively. This research proposes a phased integration model that starts with critical data elements and cores in a skeletal architecture, expanding through initial integration as the capacity for automated integrations grows, serving as a solution for analogous situations. In addressing sustained value focus, Dwivedi et al. [11] also proposed an incremental, phased implementation alongside continuous value to deal with ongoing technical complexities and a relentless focus on value.

The adoption of technology was limited to staff implementation due to concerns regarding its complexity and whether the technology being deployed was overreaching. The resolution, in this instance, was providing specific training materials aimed at resolving the issue. Training demonstrates the role of AI in transforming jobs and corroborates the position of Manoharan and Ashtikar [15], who suggest using AI as a partner, not as a subservient tool that performs functions without independent thought. This research proposes a training model that hospitality businesses can utilise to facilitate quicker employee acceptance of AI technology.

The collection and analysis of guest behavior data posed additional challenges to implementation from a privacy perspective. The framework developed during this research incorporated the privacy-by-design approach, with principles of minimization, purpose limitation, and transparent processing. These measures address the concerns about AI implementation raised by Kshetri et al. [10]. focusing on ethics. The pseudonymous protocols developed in this research enable more precise, automated algorithmic data analysis while maintaining privacy, thereby offering hotel practitioners frameworks for addressing the ethical concerns of AI in personalized service automation.

4.4 Integration with Existing Systems and Critical Evaluation

Preserving organisational issues and technological intricacies simultaneously while incorporating AI-powered loyalty optimization into pre-existing hotel management systems is a complex problem. The analysis conducted shows that successful integration goes beyond technical factors and includes workflow cohesion and organisational culture preparedness. The middleware solution devised during the work on the system, which involves building abstraction layers between the legacy systems and the emergent AI capabilities, is highly applicable to hotels that have existing technological infrastructures. This solution addresses the Phillip's and Galliers' [16, 17] concern about integration difficulties by allowing partial systems modernisation without entire systems modernisation.

Different hotel categories reveal differing returns on investment as a result of AI implementation. Luxury properties achieved the fastest return, attributable to higher average transaction values and revenue enhancement opportunities, achieving 5.8 months. However, midscale properties demonstrated positive NPV over five years, but required a longer payback period of 9.3 months. These results are consistent with Li's [18] report on revenue management and AI-driven technologies, where they highlighted implementation costs varying by category. This research's synthesised detailed methodology for ROI analysis equips hotel operators with the means to measure potential AI investments against their operational contexts and profiles of their guests.

The strengths and weaknesses of the AI-driven framework arise from the critical evaluation conducted on it. As per the analysis, the framework is capable of excellent performance with trend detection and generating bespoke recommendations based on users' historical data. Yet, its predictive accuracy suffers for users with scant histories and interactions; the "cold start" problem is still only partially resolved compared to within-methods benchmarks. Further, individual effectiveness of the framework varies across cultures, as the Asian markets respond differently to AI-driven personalization compared to Western markets. This supports Wang's [19] discussion on culturally distinct lines of variation concerning the reception and use of AI technology in hospitality, pointing toward the necessity for culturally responsive AI designs. While the framework represented an advancement compared to traditional approaches, these oversights highlight the need for more contextualisation and refinement in future iterations.

This study addresses important limitations. Within technical boundaries, there are several challenges: the cold-start problem for new customers, who require at least 3 to 5 engagements before receiving optimal recommendations; system latency of 15 minutes, which prevents real-time personalization; and a 5-9% performance drop in non-Western countries, necessitating adaptation to Western cultural norms. Methodological limitations within the study include dependence on historical data trends, which could become obsolete with the introduction of novel service offerings, overfitting hotel chain-intervention patterns in the absence of regularization, and bias due to oversampling from large hotel chains. Implementation limitations include constraints such as the need for 6 to 8 months of integration, which is often necessitated by smaller operators, as well as the risk of aggressive data gathering leading to privacy violation conflicts and the requirement for extensive staff retraining, all of which represent major operational costs.

5. Conclusion

This study illustrates the revolutionary impact of artificial intelligence on the analysis of hospitality customer behaviour and loyalty programme engagement optimization. The blended approach using deep learning and AI analytics provided sharp advancements over previous methods, achieving a 27.3% customer retention increase, a 42.1% improvement in loyalty programme participation, and an 18.5% revenue increase per loyal customer. The study contributes three overarching findings by shifting practical implementation insights gained through multi-tiered business impact measurement across hotel classes from demographic to behavioural segmentation frameworks, and offering strategies for addressing integration gaps, training gaps, and ethics gaps, which clearly indicate pre-defined, quantifiable outcomes justifying post-action evaluations. Results indicated positive ROI across all hotel classes with average payback periods of 7.4 months, NPV/Investment ratios of 4.3:1 over five years. Market adaptive responsive optimization buffer zone circumventions for customer behaviour shifts and external condition changes were optimally sustained by the framework's ability to continuously learn. This study acknowledges the need for adaptation to culture cold-start problems for customers with sparse historical data and independent property applicability as generalisable limitations. Research ought to address culturally customized AI frameworks, ethics of algorithmic customer relation management, and convergence with emerging technologies like AR and blockchain. The findings indicate that AI-powered loyalty optimization represents a fundamental industry transformation rather than incremental improvement, offering sustainable competitive advantages for early adopters in the evolving hospitality landscape.

Ethical issue

The authors are aware of and comply with best practices in publication ethics, specifically with regard to authorship (avoidance of guest authorship), dual submission, manipulation of figures, competing interests, and compliance with policies on research ethics. The author adheres to publication requirements that the submitted work is original and has not been published elsewhere.

Data availability statement

The manuscript contains all the data. However, more data will be available upon request from the authors.

Conflict of interest

The authors declare no potential conflict of interest.

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