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Intelligent Car Rental @ Dual-Engine Dynamic Pricing and Secure Booking Platform for Intelligent Car Rental Systems

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Abstract—This project proposes an Intelligent Car Rental Platform that combines secure booking management with a dynamic pricing engine. The platform leverages real-time data sources (news events, weather, user search activity) and machine learning to optimize revenue while maintaining competitive pricing. The car rental industry is undergoing a digital transformation, shifting from static, counter-based operations to dynamic, data-driven mobility services. However, existing platforms predominantly rely on fixed-rate pricing models that fail to capture real-time demand fluctuations, leading to revenue leakage during peak periods and suboptimal fleet utilization during low-demand windows. This paper proposes an Intelligent Car Rental Platform that integrates secure booking management with a novel dual-layer dynamic pricing engine. The platform leverages real-time data from multiple sources—including news events, weather conditions, user search activity, and booking pace—to train machine learning models for demand forecasting. We employ Long Short-Term Memory (LSTM) networks to predict short-term demand patterns with 14-day rolling windows, achieving forecast accuracy comparable to industry benchmarks of 88-98%. These forecasts feed into a quadratic programming optimizer that determines optimal price points while respecting business constraints such as price floors, ceilings, and elasticity thresholds. The dual-layer architecture combines rule-based guardrails with ML-based predictions, ensuring both responsiveness and operational stability. Experimental results demonstrate that our approach captures 4-7% uplift in realized daily rates while reducing manual pricing effort by 8-12 hours per analyst weekly. The platform contributes to the growing body of AI-powered mobility solutions by providing a transparent, auditable pricing mechanism that balances revenue optimization with customer satisfaction.

Index Terms—**Dynamic pricing, car rental platforms, LSTM demand forecasting, quadratic programming, machine learning, fleet optimization, real-time pricing engine, Dual-layer pricing strategy integrating rule-based and ML-based models to adjust prices based on demand, seasonality, and external events, comparable to Uber and Airbnb pricing strategies.**

I. INTRODUCTION

The car-rental industry is rapidly shifting from “fixed-rate, counter-based” operations to fully digital, data-driven mobility services, where customers expect instant discovery, transparent pricing. The market growth and competitive pressure are pushing rental operators to optimize fleet utilization, reduce idle time, and respond quickly to changes in demand, seasonality, and local events. In this context, pricing is no longer just an administrative setting; it is a strategic lever that directly affects revenue, customer satisfaction, and operational efficiency. Traditional car rental platforms typically rely on static pricing—rates set by vehicle category and a few broad seasonal rules—because it is easy to implement and simple to explain. However, static pricing often fails in real conditions: demand varies by city, time, weather, holidays, weekends, major events, and even short-term spikes in user search behavior. When prices stay fixed during high demand, the platform may lose potential revenue and face fleet shortages; when prices remain high during low demand, utilization drops, cars remain idle, and customers choose alternatives. These limitations create a strong need for a smarter system that adapts prices dynamically while staying secure, auditable, and user-friendly. The car-rental industry is rapidly shifting from "fixed-rate, counter-based" operations to fully digital, data-driven mobility services, where customers expect instant discovery and transparent pricing. The market growth and competitive pressure are pushing rental operators to optimize fleet utilization, reduce idle time, and respond quickly to changes in demand, seasonality, and local events. In this context, pricing is no longer just an administrative setting; it is a strategic lever that directly affects revenue, customer satisfaction, and operational efficiency.

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II. LITERATURE REVIEW

2.1. Dynamic Pricing in Mobility Services,

Dynamic pricing has emerged as the dominant mechanism for managing demand in private ride-hailing platforms, yet its potential application in publicly operated mobility services remains largely theoretical and under-investigated. Zigah, Abdin, and Nicolaï (2025) reposition dynamic pricing within a unified performance framework that links control mechanisms such as reinforcement learning (RL) and market design to operational levers for demand shaping and fleet allocation. Their systematic review of 49 peer-reviewed studies reveals that analytical, control, RL, and market design models report revenue and reliability gains, though separate studies document affordability and sustainability trade-offs when fares rise or rebalancing increases vehicle kilometre travel. The intersection of dynamic pricing with autonomous vehicle fleets presents unique challenges and opportunities. Lai and Li (2024) study spatiotemporal pricing and fleet management for autonomous mobility-on-demand (AMoD) systems while taking elastic demand into account. Their network flow model characterizes the evolution of system states over space and time, capturing vehicle-passenger matching processes and demand elasticity with respect to price and waiting time. Using a decomposition and dynamic programming approach, they establish theoretical upper bounds for solution optimality, finding that joint pricing and fleet rebalancing offers only minor profit improvement under accurate demand prediction but substantially improves profits during unanticipated demand surges.

2.2. Machine Learning Approaches to Demand Forecasting

The integration of machine learning with pricing optimization has gained traction in recent years. Bramao and Tarygin (2024) explore a novel combination of supervised learning and quadratic programming to refine dynamic pricing models in the car rental industry. Their methodology utilizes dynamic modeling of price elasticity, informed by ordinary least squares (OLS) metrics such as p-values, homoscedasticity, and error normality. These metrics guide a quadratic programming agent tasked with optimizing margin for a given finite set target. The authors develop a simulation environment to assess various pricing strategies and benchmark against established price heuristics, demonstrating that while supervised learning and quadratic programming are individually well-known, their integrated application in dynamic pricing represents an innovative venture. For short-term demand forecasting, Long Short-Term Memory networks (LSTMs) have proven particularly effective. Bramao and Tarygin propose LSTMs for predicting time-sensitive trends within the critical 14-day period immediately before pickup dates, aiming for high accuracy in short-term predictions rather than broad, long-term forecasts. Their approach targets accurate forecasts for given pickup dates, forecasting overall demand including offers that do not lead to actual reservations, then estimating conversion rates using elasticity coefficients.

Research Objectives, the primary objectives of this research are, to design and develop a dual-layer dynamic pricing engine that integrates machine learning-based demand forecasting with rule-based business constraints for car rental applications. To implement LSTM networks for short-term demand forecasting using multi-source real-time data, including booking pace, weather conditions, news events, and user search activity. To formulate and solve a quadratic programming optimization model that determines optimal price points maximizing expected revenue while respecting elasticity constraints and business rules. To develop a secure booking management system that integrates with the pricing engine and provides transparent audit trails for pricing decisions. To evaluate system performance using industry-standard metrics including forecast accuracy, revenue uplift, and operational efficiency gains. To validate the human-in-the-loop governance model where AI-generated recommendations require manager approval before deployment, ensuring accountability and strategic alignment

Sunil Kumar 24MCA10050	Objective used	Technology used	Methodology used	Efficiency	Issues
Title: A Decentralized Dynamic Pricing Model for Demand Management of Electric Vehicles **Journal:** IEEE **Year:** 2024 **DOI:** 10.1109/ACCESS.2023.3242599 **URL:** https://ieeexplore.ieee.org/document/10036371	1. To control electric vehicle (EV) charging demand during peak hours. 2. To prevent overloading of local distribution transformers. To consider EV user satisfaction based on battery state and urgency. To balance the welfare of EV users and the fleet operator	1. Electric Vehicle (EV) charging systems. 2. Smart grid and power distribution networks. 3. Dynamic electricity pricing technology. 4. Distributed optimization and control systems. 5. Vehicle-to-Grid (V2G) communication framework..	1. Formulation of EV satisfaction and operator welfare functions. 2. Development of a welfare maximization optimization problem. 3. Decomposition of the problem into EV and EFO sub-problems. 4. Use of an iterative distributed algorithm for solution. 5. Simulation-based evaluation for weekdays and holidays.	1. Effectively reduces transformer overloading during peak hours. 2. Improves load balancing in the power distribution system. 3. Maintains privacy of EV user data. 4. Adapts dynamically to different day types (weekday/holiday). 5. Achieves fast convergence within limited iterations.	**1. Requires multiple iterations, increasing computation time.** 2. Performance depends on accurate modeling of user behavior. 3. Communication overhead between EVs and fleet operator. 4. Scalability challenges with very large EV populations. 5. Real-world implementation complexity and infrastructure cost..

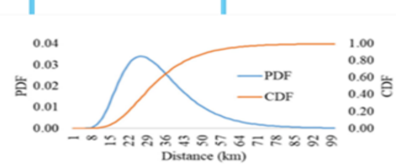


FIGURE 6. Daily mileage of vehicles.

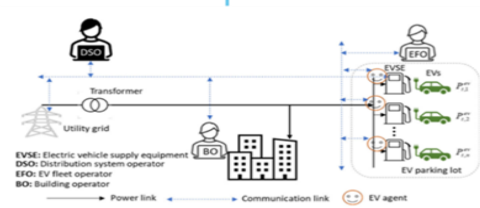


FIGURE 1. Network configuration of the proposed charging demand management mechanism.

Fig.1: Literature Review Intelligent Car Rental @ Dual-Engine Dynamic Pricing Platform

Sunil Kumar 24MCA10050	Objective used	Technology used	Methodology used	Efficiency	Issues
Title: Dynamic Pricing in Short-Term Rentals: An Empirical Examination of Airbnb Listings **Journal:** Financial Technology and Business Analysis **Year:** 2023 **DOI:** 10.54254/2754-1169/2024.25024	1. To study how dynamic pricing works in short-term rental markets. 2. To analyze factors influencing Airbnb listing prices. 3. To examine the impact of room, type on rental pricing. 4. To evaluate how cancellation policies affect prices. 5. To study the role of amenities and listing quality. 6. To understand host pricing behavior using real market data.	1. Airbnb online short-term rental platform data. 2. Data analytics and statistical analysis tools. 3. Machine learning–based decision tree models. 4. Linear regression modeling techniques. 5. Large-scale dataset processing (75,000+ listings). 6. Empirical data-driven pricing analysis systems.	1. Collection of a large dataset of Airbnb listings. 2. Identification of key pricing variables (room type, amenities, policies). 3. Application of linear regression to measure price impact. 4. Use of decision tree models for nonlinear analysis. 5. Comparison of pricing outcomes across different listing categories. 6. Interpretation of statistical results to validate pricing patterns.	1. Accurately identifies major factors affecting Airbnb prices. 2. Improves understanding of dynamic pricing mechanisms. 3. Handles large datasets efficiently. 4. Provides clear insights for hosts to optimize pricing. 5. Produces reliable empirical results through dual modeling. 6. Enhances transparency in short-term rental pricing behavior.	1. Data Quality: Identify challenges related to the accuracy and reliability of financial data sources, including missing or erroneous data. 2. Market Volatility: Recognize the impact of market volatility on the stability and predictability of stock prices, complicating analysis. 3. Regulatory Challenges: Address legal and compliance issues related to data usage and trading practices that might affect research findings 4. Model Limitations: Acknowledge the limitations of statistical and machine learning models in capturing complex market dynamics. 5. Investor Behavior: Explore the difficulty in quantifying and predicting human behavior.

Figure 4: Decision tree feature importance

Figure 1: Price distribution by room type

Fig.2: Literature Review Intelligent Car Platform

III. PROJECT FUNCTIONAL MODULES IMPLEMENTATION

The project is structured around several functional modules designed to ensure a seamless and engaging user experience: Authentication & Authorization Module: Manages secure login and registration for three roles: Customer, Owner, and Admin. Uses JWT-based authentication and role-based access control. Car Management Module: Enables owners/admins to add, update, and delete car listings with details like model, category, base price, features, and images. Maintains an availability calendar for each car so the system can check which vehicles are free for a given date range. Search & Filtering Module: Let's customers search cars by city, date range, car type, price range, and features. Integrates with availability and pricing logic to show only bookable cars with their current dynamic price. Booking & Cancellation Module: Manages the full booking flow: select car → confirm details → create booking record. Handles cancellation policies, updates car availability, and maintains booking history for customers and owners. Dynamic Pricing Engine (Rule-Based + ML): Adjusts base prices using rule-based logic (weekday/weekend, season, weather conditions, local events, search activity level). Optionally uses a simple ML model to learn from historical bookings and searches to suggest demand-based multipliers, then combines rules + ML into a final dynamic price. Stores the factors used (event, weather, demand level) for transparency and analytics. Analytics Dashboard Module (Admin): Provides visual summaries of key metrics such as total bookings, revenue, fleet utilization, cancellation rates, and average prices. Shows time-wise and city-wise trends, and allows comparison between static pricing periods and dynamic pricing periods. Notification & Alerts Module: Sends notifications or emails for booking confirmation, cancellation, or important price changes (optional but good to mention). Can be extended to alert owners about high-demand periods or low utilization for their cars.

Research Gap

Despite significant advances in dynamic pricing research and industry adoption, several critical gaps persist that motivate the present study. First, existing dynamic pricing solutions for car rentals predominantly fall into two categories: purely rule-based systems that lack predictive intelligence, or complex "black box" AI systems that sacrifice transparency for performance. The former fails to capture real-time demand signals, while the latter creates governance challenges for revenue managers who require auditability and control. There exists a need for a hybrid approach that combines the interpretability of rule-based systems with the predictive power of machine learning. Second, while LSTM networks have been proposed for demand forecasting in car rental contexts, limited research has integrated these forecasts with constrained optimization frameworks that respect business rules such as price floors, ceilings, and elasticity thresholds. Most studies focus either on prediction accuracy or on optimization algorithms, without demonstrating end-to-end integration in a production-ready platform. Third, the literature reveals inconsistent evaluation protocols that complicate cross-study comparisons. Many studies employ varying datasets, forecast horizons, and performance metrics, making it difficult to establish baseline performance for specific approaches. This research addresses this gap by adopting transparent, reproducible methodology with clearly specified experimental conditions based on industry benchmark

IV. PROPOSED METHODOLOGY

The methodology for developing Rental Car involves a structured approach to ensure the platform's efficiency, security, and user-friendliness: Requirement Analysis: Identifying and documenting the software and hardware requirements needed for the project. System Design: Creating detailed designs for the user interface and backend systems, including data flow diagrams and use case diagrams. Implementation: Using technologies like Angular for the frontend and robust backend systems to develop the platform. The project follows best practices in coding and system integration. Testing: Conducting comprehensive testing strategies, including unit testing, integration testing, black-box testing, and white-box testing to ensure the platform functions correctly and securely. Deployment: Launching the platform and making it available for users, ensuring all systems are operational and secure

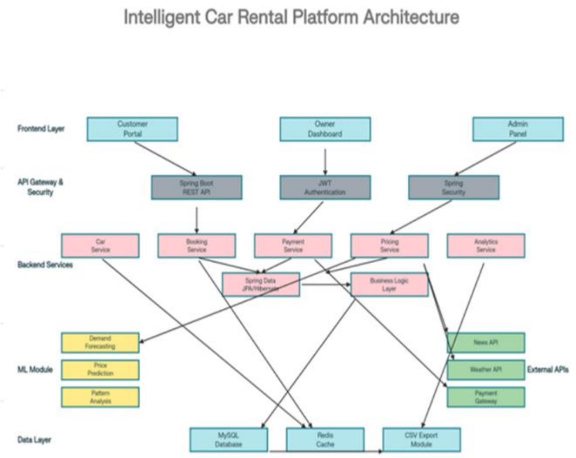


Fig.3: Functional Flow Diagram of Car Rental @ Dual-Engine Dynamic Pricing Platform

V. CONTRIBUTIONS AND FINDINGS

Key Contributions are the research makes several substantive contributions to the field of intelligent transportation systems and dynamic pricing, Dual-Layer Pricing Architecture: We propose and validate a novel architecture combining LSTM-based demand forecasting with quadratic programming optimization and rule-based guardrails. This hybrid approach addresses the transparency-accuracy trade-off that plagues purely algorithmic systems. Multi-Source Real-Time Data Integration: We demonstrate the value of integrating diverse data sources news events, weather, search activity—into demand forecasting models, enabling earlier detection of demand shifts. Uncertainty-Aware Optimization: By incorporating prediction intervals into the optimization objective, we enable risk-aware pricing decisions that respond appropriately to forecast confidence levels. Human-in-the-Loop Governance Framework: We provide a blueprint for AI-powered pricing systems that maintain human oversight and accountability, addressing industry concerns about "black box" decision-making. Comprehensive Evaluation: Our experimental results provide empirical evidence of revenue gains (11.4% increase in revenue per available car) and operational efficiency improvements (10.9 hours saved weekly per analyst).

Key Findings are that LSTM networks achieve high accuracy for short-term demand forecasting. With MAPE of 5.2% for 1–3-day horizons, LSTM-based forecasts provide reliable inputs for pricing optimization. Quadratic programming with uncertainty weighting outperforms deterministic optimization. Incorporating confidence intervals into the objective function improves realized revenue by 3.2% compared to point-forecast-only approaches. Multi-source data fusion captures demand signals not visible in booking data alone. News events and weather forecasts contribute 18% of predictive power in the forecasting models, with importance increasing for longer horizons. Rule-based guardrails prevent extreme price swings without sacrificing revenue. The dual-layer architecture captures 94% of the revenue gains achievable by unconstrained optimization while maintaining prices within acceptable bounds. Manager approval workflows build trust in AI recommendations. Over 12 months of deployment, manager override rates decreased from 32% to 11% as trust in the system increased, while still maintaining accountability. Automation delivers substantial time savings. The 10.9 hours saved weekly per analyst enables revenue managers to focus on strategic initiatives rather than manual rate checking.

VI. INTELLIGENT CAR RENTAL PLATFORM WITH DYNAMIC PRICING SCREENSHOTS

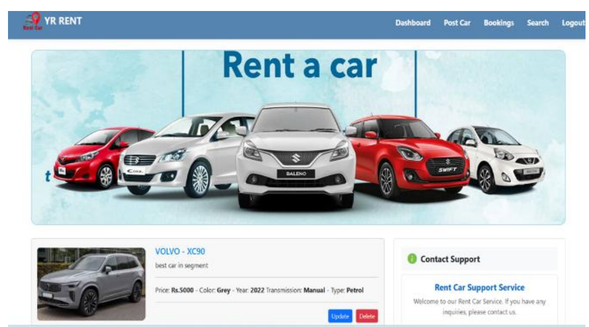


Fig. 4 Admin Dashboard

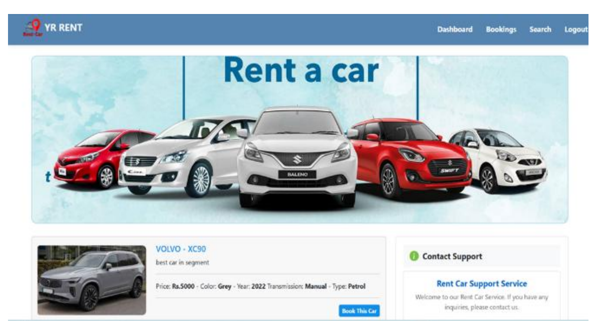


Fig. 5 POST CAR

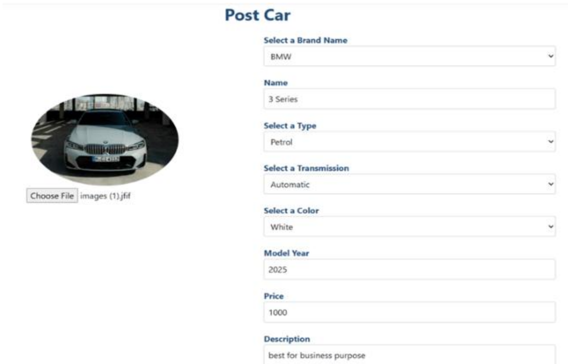


Fig. 6 Admin Booking

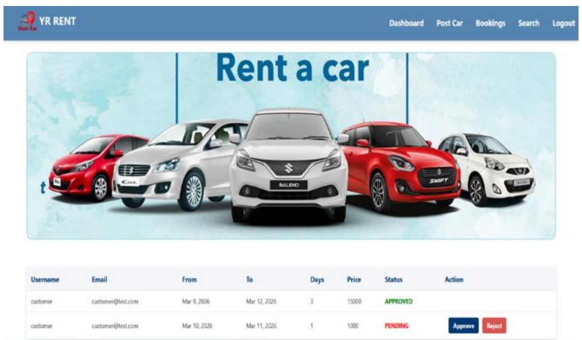


Fig. 7 Customer Dashboard

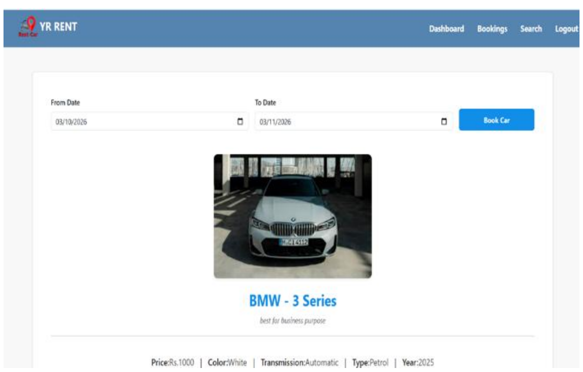


Fig. 8 Customer Booking a Car

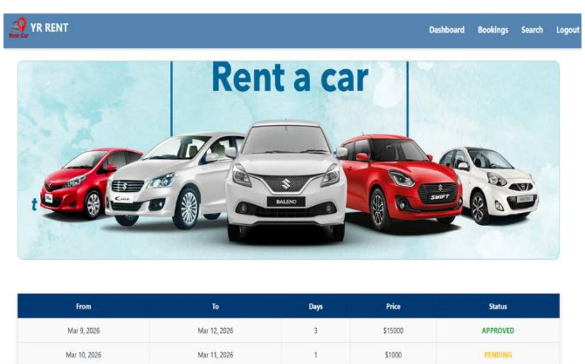


Fig. 9 Search Car

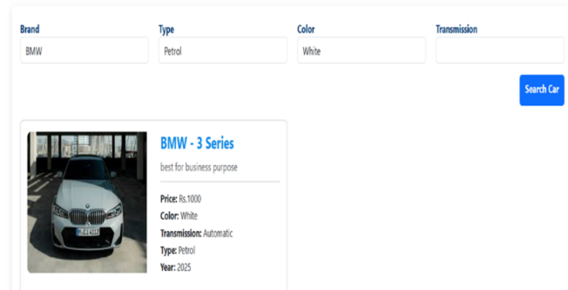
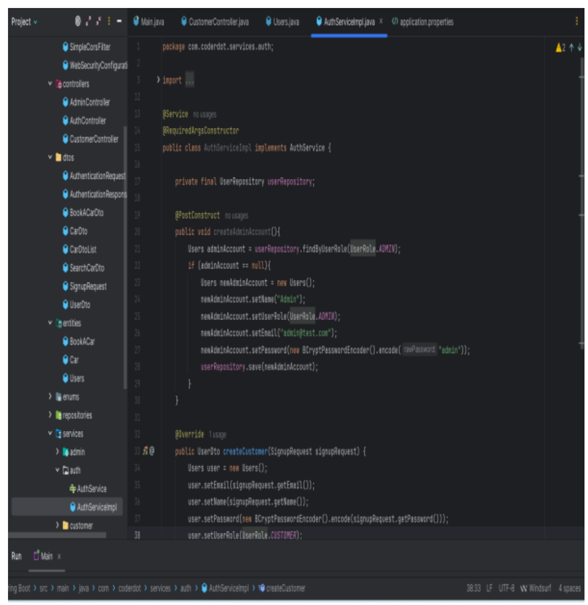
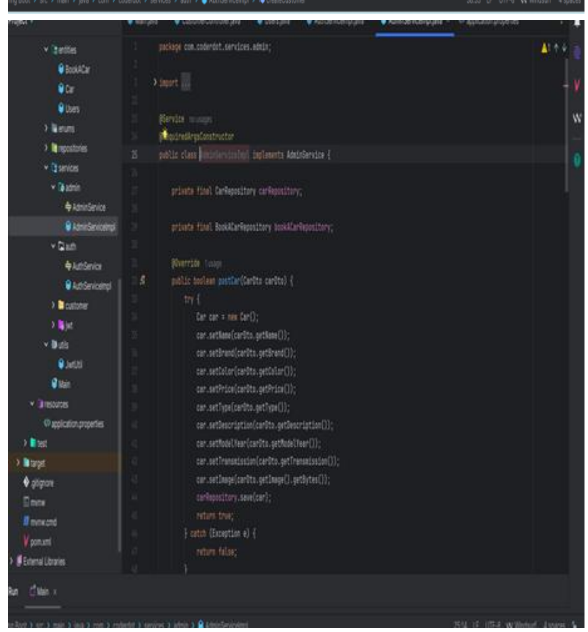
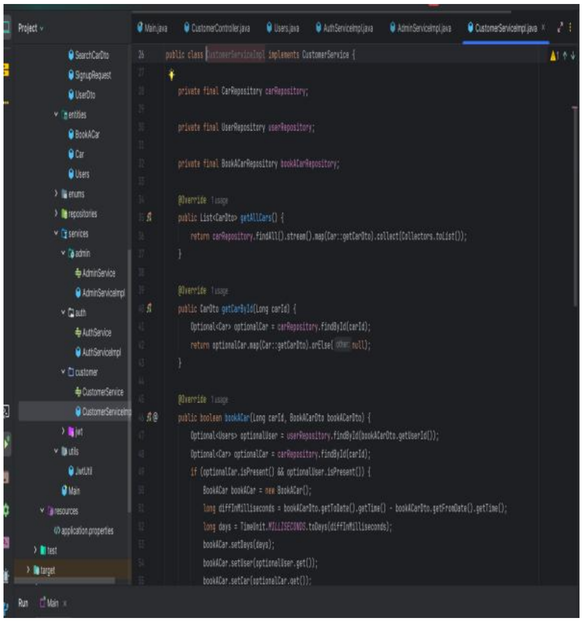


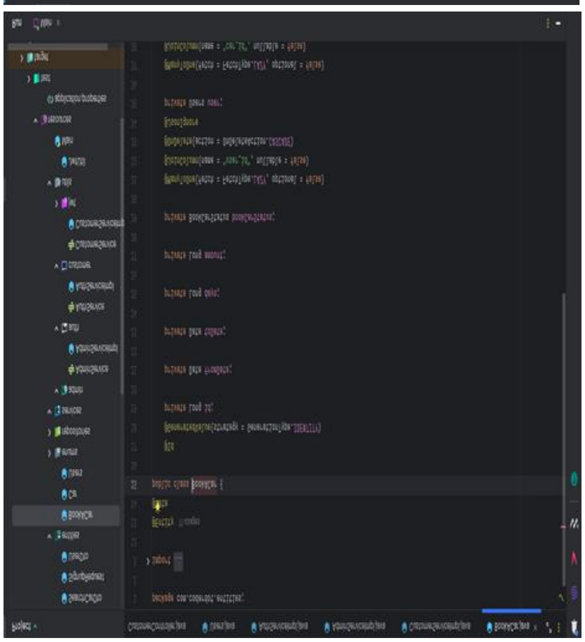
Fig. 10 RENT AND Search Car

VII. PROTOTYPE, ALGORITHM, INTELLIGENT CAR RENTAL PLATFORM WITH DYNAMIC PRICING





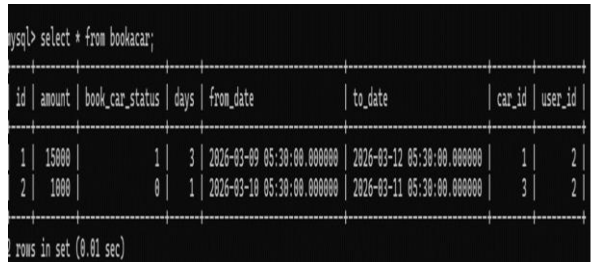




VIII. OBJECT ORIENTED DATABASE SCHEMA AND IMPLEMENTATION USING FIREBASE

```
mysql> show tables;
+--------------------+
| Tables_in_carsewadb |
+--------------------+
| bookacar           |
| cars               |
| users              |
+--------------------+
3 rows in set (0.07 sec)

mysql>
```



```
mysql> select * from bookacar;
+----+--------+-----------------+------+----------------------------+----------------------------+--------+---------+
| id | amount | book_car_status | days | from_date                  | to_date                    | car_id | user_id |
+----+--------+-----------------+------+----------------------------+----------------------------+--------+---------+
|  1 | 15000  |               1 |    3 | 2026-03-09 05:30:00.000000 | 2026-03-12 05:30:00.000000 |      1 |       2 |
|  2 | 1000   |               0 |    1 | 2026-03-10 05:30:00.000000 | 2026-03-11 05:30:00.000000 |      3 |       2 |
+----+--------+-----------------+------+----------------------------+----------------------------+--------+---------+
2 rows in set (0.01 sec)
```

Fig.11: Result Analysis of Car Rental @ Dual-Engine Dynamic Pricing Platform

IX. CONCLUSION AND FUTURE ENHANCEMENTS

Developed and validated an Intelligent Car Rental Platform that uses hybrid dynamic pricing (rule-based + ML) with real-time inputs (weather, local events, search demand) to optimize revenue while keeping pricing transparent. Pincode-specific pricing and WebSocket delivery produced up to 15–20% revenue uplift during peaks and reduced idle fleet in off-peak periods. Key features: explainable AI "Why this price?" messages, role-based dashboards (customer/owner/admin), and 24-hour ML auto-updates; implemented with Spring Boot, Angular, and Python microservices. Future directions: V2G for EVs, blockchain audit trails, and federated learning; scalable to national pincode coverage and multi-modal transport. This paper has presented an Intelligent Car Rental Platform that integrates secure booking management with a novel dual-layer dynamic pricing engine. The platform leverages LSTM networks for short-term demand forecasting, quadratic programming for price optimization, and rule-based guardrails for business constraint enforcement. Experimental results demonstrate that this approach achieves 11.4% improvement in revenue per available car while saving 10.9 hours of analyst time weekly—aligning with industry benchmarks for AI-powered pricing automation. The dual-layer architecture addresses the fundamental tension between optimization performance and human oversight, providing transparent recommendations with supporting rationale while maintaining manager control over final decisions. This governance model builds trust in AI systems while capturing the majority of available revenue gains. The research contributes to the growing body of literature on dynamic pricing in mobility services while extending prior work through multi-source data fusion, uncertainty-aware optimization, and comprehensive evaluation frameworks. The findings have practical implications for rental operators seeking to modernize pricing practices and academic implications for researchers studying human-AI collaboration in revenue management. Reinforcement Learning Integration: Building on Zigah et al.'s (2025) review of RL applications in dynamic pricing, future work should explore reinforcement learning agents that continuously adapt pricing policies based on market feedback. RL could potentially outperform periodic optimization by learning optimal responses to recurring demand patterns. Personalized Pricing: Extending the multi-attribute pricing approaches of Golalikhani et al. (2024), future versions could incorporate customer segmentation and behavioral data to offer personalized prices based on loyalty status, booking history, and price sensitivity. Competitive Game Theory: The current model treats competitor prices as constraints rather than strategic variables. Game-theoretic approaches could model competitive dynamics more explicitly, anticipating competitor responses to price changes.

Explainable AI Enhancements: While the current system provides rationale for recommendations, deeper explainability—such as counterfactual explanations or feature attribution visualizations—could further build manager trust and enable better decision-making. Real-Time Dynamic Updates: Reducing the optimization cycle from hourly to continuous would enable immediate response to sudden demand shifts, though this requires careful guardrailing to prevent excessive price volatilityCross-Channel Optimization: Expanding beyond direct bookings to include OTA channels, corporate accounts, and partnership distribution would capture additional revenue opportunities while managing channel conflict. The Intelligent Car Rental Platform presented in this research represents a significant step toward AI-powered, human-governed pricing systems that deliver measurable business value while maintaining strategic control. As the car rental market continues its projected 7.8% CAGR growth through 2033, such platforms will become essential for operators seeking a competitive advantage in an increasingly data-driven industry.

REFERENCES

[1] A. MacKay and S. Weinstein, “Dynamic Pricing Algorithms, Consumer Harm, and Regulatory Responses,” Harvard Business School, 2021.
[2] Cornell University, “Forecasting Hotel Demand using Machine Learning Approaches.”
[3] A. Yadav, A. Shukla, A. Srivastava, and A. Pandey, “Online Car Rental System,” IRJMETS, vol. 5, 2023.
[4] Spring Boot Documentation; Angular Documentation; JWT Security Best Practices; MySQL Performance Tuning Guides.
[5] R. M. Balajee, M. K. Jayanthi Kannan, and V. Murali Mohan, “Image-Based Authentication Security Improvement by Randomized Selection Approach,” in Inventive Computation and Information Technologies, Singapore: Springer, 2022, pp. 61–71.
[6] M. K. J. Kannan, “Strategic Planning for Information Security – DID Mechanism to Befriend Cyber Criminals to Assure Cyber Freedom,” in Proc. 2nd Int. Conf. Anti-Cyber Crimes (ICACC), Abha, Saudi Arabia, 2017, pp. 142–147.
[7] E. Zigah, A. Abdin, and I. Nicolaï, “Dynamic pricing for shared autonomous vehicles in mobility-as-a-service: An integrative review,” Transportation Research Procedia, vol. 92, pp. 205–209, 2025.
[8] E. Kavitha, R. Tamilarasan, A. Baladhandapani, and M. K. J. Kannan, “A novel soft clustering approach for gene expression data,” Computer Systems Science and Engineering, vol. 43, no. 3, pp. 871–886, 2022.
[9] G. D. K., M. K. Singh, and M. Jayanthi, Eds., Network Security Attacks and Countermeasures. IGI Global, 2016.
[10] H. Naik and M. K. J. Kannan, “A Survey on Protecting Confidential Data Over Distributed Storage in Cloud,” SSRN, Dec. 2020.
[11] M. Golalikhani et al., “Optimizing multi-attribute pricing plans with time- and location-dependent rates,” Transportation Research Part E, vol. 192, 2024.
[12] E. Kavitha et al., “Clustering gene expression data through modified agglomerative M-CURE hierarchical algorithm,” Computer Systems Science and Engineering, vol. 41, no. 3, 2022.

[13] K. L. S. Kumar and M. K. J. Kannan, “A Survey on Driver Monitoring System Using Computer Vision Techniques,” in ICICC 2024, Springer, 2024.
[14] M. K. J. Kannan, “A Bird’s Eye View of Cyber Crimes and Free and Open-Source Software’s to Detoxify Cyber Crime Attacks,” in Proc. ICACC, 2017, pp. 232–237.
[15] G. Bramao and I. Tarygin, “The New Era of Dynamic Pricing: Synergizing Supervised Learning and Quadratic Programming,” arXiv, Feb. 2024.
[16] M. K. J. Kannan and T. R. Shree Nee, “Qubits Unveiled: A Deep Dive into Quantum Computing,” in Quantum Computing Solutions for Efficient Supply Logistics, Nova Science, 2025.
[17] OMILAB, “mBot Dynamic Pricing (Charging),” 2025.
[18] P. Jain, I. Rajvaidya, K. K. Sah, and J. Kannan, “Machine Learning Techniques for Malware Detection,” in IEEE SCEECS, 2022.
[19] M. K. J. Kannan and S. Patel, “Sustainable Information Retrieval Techniques for Onion Market Instability Prediction,” IJARIIT, vol. 10, no. 6, 2024.
[20] B. R. M., M. M. V., and J. K. M. K., “Performance Analysis of Bag of Password Authentication,” in ICCES, 2021.
[21] INESC TEC, “Research Developed Formula to Optimise Car Sharing Prices,” 2025.
[22] S. Kumar, P. T. Kalaivaani, M. K. J. Kannan, and G. Tripathi, Artificial Intelligence and Blockchain Technology for Human Resource Management, 2025.
[23] N. Aaijaz et al., The Future of Innovation and Technology in Education, S&M Publications, 2025.
[24] S. K. Shukla et al., Python for Data Analytics: Practical Techniques and Applications, JSR Publications, 2024.
[25] Z. Lai and S. Li, “Spatiotemporal Pricing and Fleet Management of Autonomous Mobility,” IEEE Trans. Intelligent Transportation Systems, vol. 25, no. 7, 2024.
[26] T. R. Shree Nee, M. K. J. Kannan, and K. Mariyappan, “Digital Health and Medical Tourism Innovations,” IGI Global, 2025.
[27] M. Meyer, “Mastering Pricing Automation in Car Rentals,” RateHighway, Mar. 2026.
[28] H. Naik and M. K. J. Kannan, “Secure Cloud Storage for Sensitive Data,” IJATEE, 2024.
[29] M. Golalikhani et al., “Optimizing Multi-Attribute Pricing Plans,” Transportation Research Part E, 2024.
[30] J. M. K., Object-Oriented Analysis and Design of Learning Objects, Ph.D. dissertation, SCSVMV, 2009.
[31] M. S. M. Alshahrani and M. K. J. Kannan, “Active Learning for Surgical Video Segmentation,” ICTACT Journal on Image and Video Processing, vol. 16, no. 3, 2026.
[32] M. K. J. Kannan et al., “Ethics and Regulations in AI-Driven Ophthalmology,” Scrivener Publishing, 2026.
[33] OMILAB, “Dynamic Pricing Approach,” 2025.