Data-Driven Insights for Railway Operations: Exploring Customer Behavior, Revenue Trends, and Delay Predictions

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***Abstract*— Railway transportation is a centerpiece of public transit systems, enabling efficient mobility for millions of passengers daily. This study analyzes 31,653 railway transactions to uncover trends in customer behavior, operational efficiency, and revenue generation. Through exploratory data analysis, key insights emerged, such as the dominance of online ticket purchases, significant revenue concentration on top routes like London Kings Cross to York, and delays primarily caused by signal failures, which affect 15% of journeys. Predictive modeling, using machine learning techniques such as Random Forest, was applied to forecast actual arrival times to enhance operational decision-making. The model had high accuracy, showing its utility for improving delay communication and operational planning.**

Based on these, actionable recommendations are suggested: optimizing train schedules to mitigate delay issues during peak hours, optimizing refund processes to increase customer satisfaction, and applying predictive models toward real-time improvements. It therefore emphasizes the importance of information-driven insights into addressing railway challenges while improving passenger experience. Future work can be done on integrating exogenous factors such as weather and infrastructure condition to have better predictions and operational strategies. This analysis provides a basis on how railway management can be done with the help of data analytics and predictive modeling.

Keywords*— *railway analytics, customer behavior, revenue optimization, delay predictions, machine learning.

I. Introduction

The railway is one of the core modes of public transportation systems around the world, providing millions of passengers with affordable and efficient travel each day. In countries such as the United Kingdom, railways provide vital links between major cities, economic centres, and rural areas. Reliability, affordability, and efficiency of railway services are crucial to assure passenger satisfaction and operational performance for economic growth [1] [6] [11]. Nevertheless, the sector remains plagued by perennial problems such as delays, inconsistent pricing strategies, revenue optimization, and growing customer dissatisfaction [3] [12].

These challenges highlight the need for innovative, data-driven solutions to improve decision-making and operational efficiency [5] [12]. Modern rail systems generate rich datasets, capturing ticket purchases, journey details, and delay information, which provide opportunities to uncover actionable insights through advanced data analytics. Analyzing such data can help railway operators understand customer behavior, identify revenue trends, and assess causes of delays, enabling them to address inefficiencies and improve overall service quality[1] [4] [11].

Capabilities further extend to predictive analytics enabled by machine learning, which can estimate arrival times, proactively handle delays, and even optimize pricing strategies [2] [3] [5]. Various research has shown that the use of artificial intelligence in railway systems can reduce delays and enhance operational decision-making through better integration of real-time data [2] [5]. Data-driven insights also allow railway companies to design customer-oriented policies, such as refund mechanisms, to improve passenger trust and retention [6] [10]. This study uses data analytics and predictive modeling to identify solutions to important railway transportation challenges and provide actionable recommendations for operational improvement.

This report focuses on a comprehensive analysis of a dataset containing 31,653 records of railway transactions. The dataset includes information about ticket purchases (e.g., class, type, price), journey details (e.g., departure/arrival times, delays, and reasons for delays), and customer behavior (e.g., refund requests, purchase timing). Using exploratory data analysis (EDA) and predictive modeling, this study seeks to address the following key questions:

1. What are the major trends in customer behavior and ticket purchases?
2. Which routes and ticket types generate the most revenue?
3. What are the primary causes of delays, and how can they be mitigated?
4. Can machine learning models predict arrival times accurately to improve scheduling?

The findings of this work reveal significant patterns, such as the dominance of online ticket purchases, high revenue from advance tickets, and signal failures as a leading cause of delays. Predictive models, such as Random Forest, achieved high accuracy in forecasting arrival times, emphasizing the importance of scheduled arrival and departure times as key predictors. These insights provide practical recommendations for railway management to enhance operations, optimize schedules, and improve customer satisfaction.

CONTRIBUTIONS

This research contributes to improving the understanding and management of railway operations in a number of ways.

- Data Analysis:

  A comprehensive exploratory analysis of railway transactions was conducted; it indicated critical patterns such as dominance in the form of online ticket purchases by customers and peak-hour traveling trends. The analysis also highlighted revenue distribution across routes and ticket types, providing insights into customer preferences and operational performance. Besides this, it pinpointed key delay trends, offering further insight into the challenges involved with punctuality and passenger satisfaction.

- Revenue Insights:

  The study identified some top revenue-generating routes, which were London Kings Cross-York, and analyzed ticket type impacts on revenue to derive key actionable strategies concerning price model optimization and encouragement of advance booking, which will maximize the revenue without sacrificing customer satisfaction.

- Predictive Modeling:

  A machine learning model using Random Forest was developed to predict actual arrival times with high accuracy. This model highlighted critical factors in determining the arrival times and demonstrated the potential of predictive analytics in reducing delays and improving schedule reliability.

- Delay Management:

  With data-driven insights, the study identified the usual causes of delays, including signal failures, and provided recommendations aimed at overcoming operational inefficiencies and enhancing punctuality.

- Future Directions:

  Proposals were made to integrate real-time data and advanced analytics into railway management systems, underlining the need for collaboration with railway companies to enhance overall service quality and passenger experience.

II. BACKGROUND AND RELATED WORKS

2.1 Background

Railway systems are integral to global transportation networks, facilitating the movement of passengers and goods. However, they face persistent challenges, including operational delays, revenue management complexities, and evolving customer expectations. Addressing these issues is crucial for enhancing service quality and operational efficiency.

- Operational Delays:

  Delays in train schedules can result from various factors such as infrastructure failures, adverse weather conditions, and operational inefficiencies. These delays not only disrupt passenger plans but also propagate through the network, affecting subsequent services and overall system reliability.

- Revenue Management:

  Optimizing revenue involves strategic pricing, demand forecasting, and resource allocation. Traditional methods may not effectively capture dynamic market conditions, leading to suboptimal pricing strategies and revenue losses.

- Customer Experience:

  Modern passengers expect timely information, seamless ticketing processes, and efficient refund mechanisms. Failure to meet these expectations can diminish customer satisfaction and loyalty.

Advancements in data analytics and machine learning offer opportunities to tackle these challenges by providing deeper insights into operational patterns and enabling predictive capabilities.

2.2 Related Work

Extensive research has been conducted to improve railway operations through data-driven approaches. This section reviews key studies in customer behavior analysis, delay prediction, and revenue optimization, highlighting their contributions and limitations.

- Customer Behavior Analysis:

  Understanding passenger behavior is vital for tailoring services and enhancing satisfaction. A study by [D. Mishra, R. Panda, 2023] utilized sentiment analysis on passenger feedback to identify areas for service improvement in the Indian rail transport sector. By combining lexicon analysis with a Naïve Bayes classifier, the study provided actionable insights into customer experiences [1].

- Delay Prediction:

  Accurate prediction of train delays enables proactive management and mitigation strategies. [P. Lapamonpinyo, S. Derrible and F. Corman, 2022] developed a real-time delay prediction model using machine learning techniques such as Random Forest and Gradient Boosting. The model demonstrated improved prediction accuracy by incorporating real-time data [2].

. Similarly, [Dawale, N.N., Nandgave, S, 2023] proposed a spatiotemporal graph convolutional network to predict train delays, effectively capturing complex spatial and temporal dependencies [3].

- Revenue Optimization:

  Optimizing ticket pricing and understanding demand elasticity are critical for revenue management. [Martin Huber, Jonas Meier, Hannes Wallimann, 2022] assessed the impact of discount rates on train ticket demand using causal machine learning methods. The study provided insights into how varying discount levels influence purchasing behavior, informing dynamic pricing strategies[4].

Applications of Artificial Intelligence in Railway Operations:

The integration of AI in railway infrastructure has been explored to enhance maintenance and operational efficiency. A comprehensive review by [W. Phusakulkajorn, A. Núñez, H. Wang, A. Jamshidi, A. Zoeteman, B. Ripke, R. Dollevoet, B. De Schutter, Z. Li, 2023] examined the application of AI techniques in monitoring and maintaining railway components, highlighting the potential for predictive maintenance and improved safety [5].

Challenges and Limitations in Existing Studies:

While these studies contribute significantly to railway analytics, certain limitations persist:

- Data Limitations:

  Many studies rely on limited datasets, which may not capture the full variability of real-world operations.

- Model Generalizability:

  Models trained on specific routes or conditions may not generalize well across different networks or unforeseen scenarios.

- Integration of Real-Time Data:

  The dynamic nature of railway operations necessitates the incorporation of real-time data for accurate predictions, which is often lacking.

- Comprehensive Approaches:

  Few studies adopt a holistic approach that simultaneously addresses customer behavior, delay prediction, and revenue optimization.

Our Contribution:

Building upon existing research, this study offers a comprehensive analysis of railway operations by:

- Integrating Multiple Analytical Approaches:

  Combining exploratory data analysis with machine learning to provide a multifaceted understanding of operations.

- Utilizing a Rich Dataset:

  Leveraging a dataset encompassing 31,653 records to capture diverse aspects of railway transactions.

- Providing Actionable Insights:

  Delivering practical recommendations for enhancing operational efficiency, customer satisfaction, and revenue management.

By addressing the identified gaps, this work aims to advance the application of data analytics in railway operations, contributing to more resilient and customer-centric services.

III. Methodology and Analysis

3.1 Dataset Overview

The dataset used in this study comprises 31,653 records of railway transactions, including attributes such as ticket purchases, journey details, delays, and customer behavior. Key attributes include:

- Ticket Details:

  Ticket type, class, and price.

- Journey Information:

  Departure and arrival times, stations, and reasons for delays

- Customer Behavior:

  Purchase method, timing, and refund requests.

Each record provides a granular view of the transaction, allowing for a detailed analysis of customer behavior, revenue trends, and delay patterns. The dataset also contains features critical for predictive modeling, such as departure and arrival times, which enable forecasting arrival times.

3.2 Data Cleaning and Preprocessing

To ensure data quality, the following steps were undertaken:

1) Handling Missing Values:

   - Missing values in Reason for Delay were replaced with "On Time", as delays are irrelevant for on-time journeys and rows with critical missing values, such as ticket prices or station details, were removed.

2) Standardizing Time Columns:

   - Departure Time, Arrival Time, and Actual Arrival Time were converted to numeric values (minutes past midnight) using the lubridate package in R.

3) Categorical Encoding:

   - Features such as Ticket Type, Journey Status, and Reason for Delay were converted to factors to facilitate analysis and modeling.

Figure 1: Online vs Station: Ticket Purchase

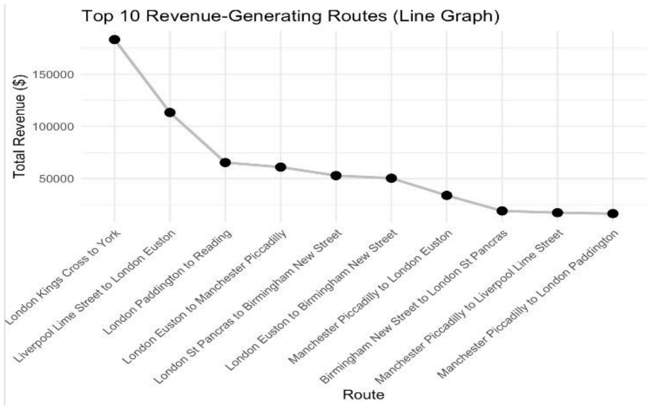

Figure 3: Top 10 Revenue-Generating Routes

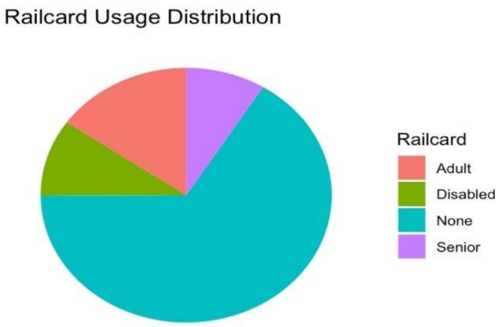

Figure 2: Railcard Usage Distribution

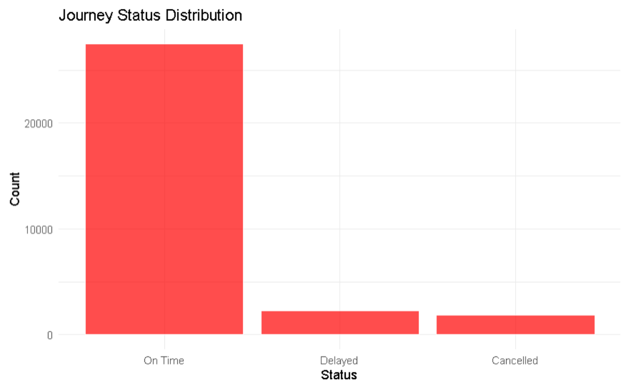

Figure 4: Journey Status Distribution

4) Outlier Detection:

- Ticket prices exceeding £200 were flagged as potential outliers and excluded from specific analyses to ensure model robustness.

  Outcome: A clean dataset suitable for exploratory analysis and machine learning, with all attributes correctly formatted and validated.

3.3 Exploratory Data Analysis (EDA)

EDA was conducted to uncover patterns and insights within the dataset. Key findings include:

1) Customer Behavior:

- Online Purchases Dominate:

  Fig 1 shows approximately 60% of tickets are purchased online, with a significant portion bought on the day of travel.

- Railcard Usage:

  Railcards are used in 30% of transactions, primarily for standard-class tickets (as shown in Fig 2).

2) Revenue Trends:

- Top Routes:

  The London Kings Cross to York route contributes the most revenue (£183,193), followed by London Paddington to Liverpool Lime Street (as shown in Fig 3).

- By Ticket Class:

  Advance tickets constitute the largest share of revenue, accounting for 41.7% of the total, followed by Off-Peak (30.1%) and Anytime (28.2%). This dominance highlights the popularity of advance bookings among passengers, likely due to discounted pricing and the ability to plan travel ahead. Encouraging the use of advance tickets can help maximize revenue while ensuring better capacity planning for railway operators.

3) Delays:

- As shown in fig 4, 15% of journeys experience delays or cancellations, with signal failures being the leading cause.

- On-time journeys accounted for 85% of the dataset, reflecting a generally reliable service but with room for improvement.

4) Average Ticket Price by Type and Class:

- Ticket class significantly influences the average ticket price across all types. For Advance tickets, the average price is $37.92 for First Class and $15.34 for

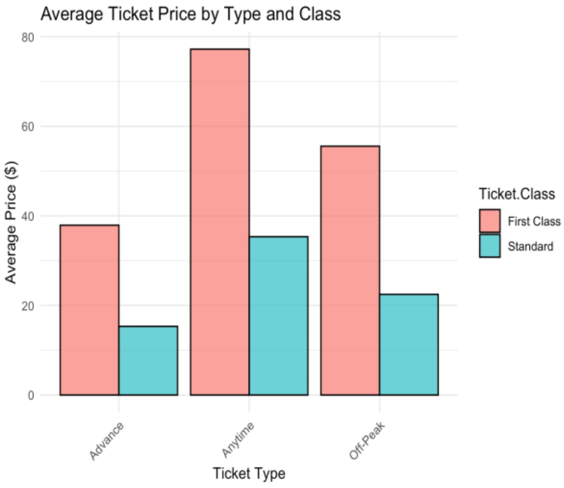

Figure 5: Average Ticket Price by Type and Class

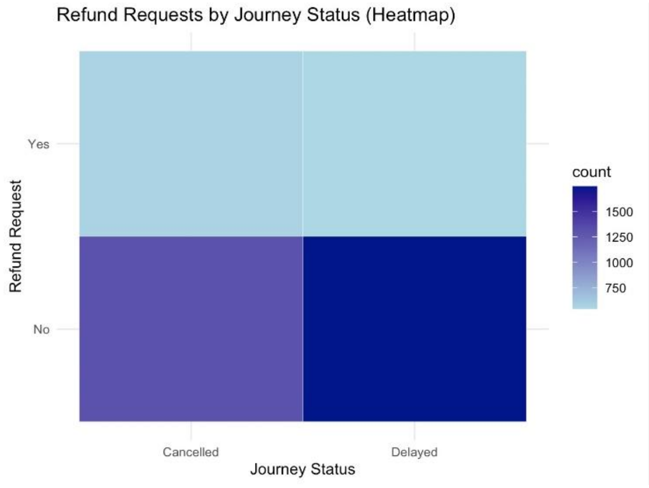

Figure 6: Refund Requests by Journey Status

Standard Class, emphasizing the affordability of advance options for standard travellers. Anytime tickets have the highest average price, with $77.23 for First Class and $35.35 for Standard Class, reflecting their flexibility for last-minute travel. Off-Peak tickets balance affordability and flexibility, with averages of $55.56 for First Class and $22.48 for Standard Class (shown in fig 5).

- These insights indicate a clear segmentation of passengers based on budget and travel needs, allowing operators to tailor pricing strategies effectively.

5) Top 5 Departure Stations:

   - The busiest departure stations include Manchester Piccadilly, London Euston, Liverpool Lime Street, London Paddington, and London Kings Cross, with Manchester Piccadilly leading in departures.
   - These stations form key hubs in the railway network, contributing significantly to passenger volume and revenue. Understanding these hubs' dynamics can help operators allocate resources efficiently and prioritize service improvements.

3.4 Refund Request Analysis

Here, we analysed the importance of understanding refund trends. Refund trends play a pivotal role in railway management as they directly influence both customer satisfaction and operational efficiency. Refund requests, while indicative of passenger dissatisfaction, also serve as an opportunity for railway operators to identify service gaps, streamline processes, and improve trust. Understanding refund patterns can reveal insights into passenger behavior, especially in cases of delays or cancellations, and highlight areas for policy improvement.

Refunds not only impact revenue but also reflect the effectiveness of the refund process and customer awareness. For instance, passengers often hesitate to file refund requests due to cumbersome procedures or lack of knowledge about eligibility criteria. As observed in previous studies, simplifying refund processes and providing real-time notifications significantly enhance customer engagement and satisfaction [6 -7]

In this study, our dataset reveals that only 3.5% of all transactions include refund requests, indicating a potentially underserved customer segment. Furthermore, in cases of delays or cancellations, only 27% of affected passengers have requested refunds, leaving a significant portion of eligible passengers unserved. The heatmap (Figure 6) illustrates the relationship between Journey Status (Cancelled or Delayed) and Refund Requests (Yes or No). From the data, it is evident that a majority of passengers do not request refunds even when eligible. Specifically, for cancelled journeys, only 30% (572 out of 1880) requested refunds, while for delayed journeys, the proportion is even lower at 24% (546 out of 2292).

The darker areas in the heatmap, representing "No Refund Requests" for both delayed and cancelled journeys, highlight that most passengers either are unaware of their eligibility or find the refund process inconvenient. This finding underscores the need for railway operators to simplify refund processes and enhance communication about refund policies to improve passenger satisfaction and trust. These findings suggest that railway operators may benefit from revisiting their refund policies and improving passenger communication.

Why Refund Trends Matter

1. Passenger Experience: Refund requests are often tied to negative experiences such as delays or cancellations. A well-structured refund policy can mitigate dissatisfaction and encourage passengers to continue using the service [8].
2. Revenue Management: While refunds impact revenue, they also highlight critical issues affecting operational reliability. By addressing these issues, operators can reduce refund claims in the long run.
3. Trust and Loyalty: Simplifying refund processes and increasing transparency build trust, ensuring passengers feel valued and more likely to remain loyal to the service[9-10].

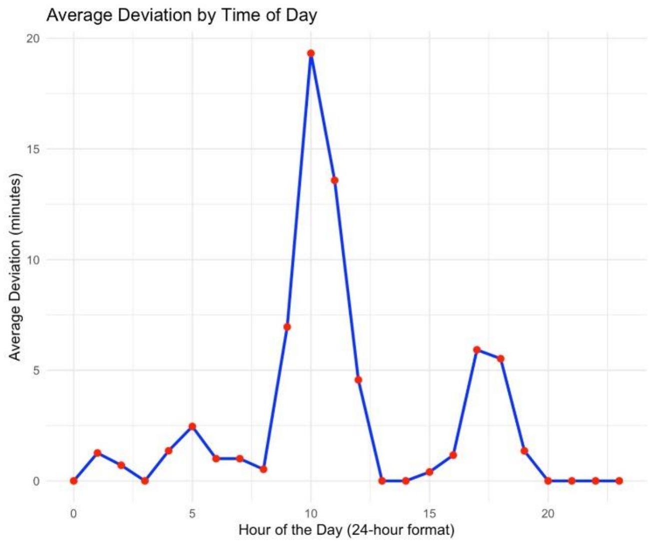

Figure 7: Average Deviation by Time of Day

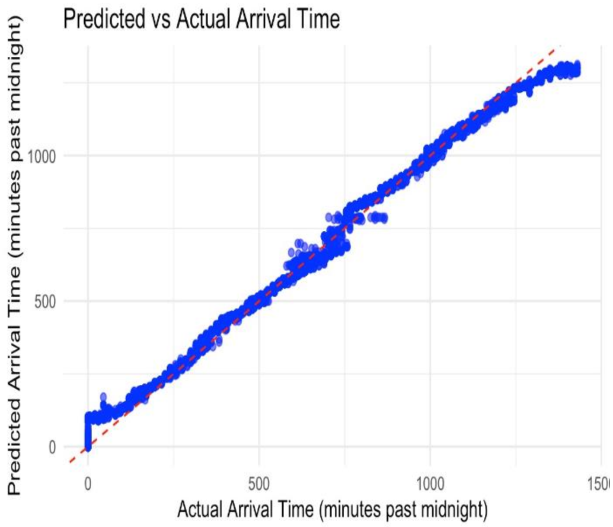

Figure 8: Predicted vs Actual Arrival Time

Current Challenges

- Complex Processes: Refund policies may be difficult to navigate, deterring passengers from filing claims.
- Lack of Awareness: Passengers may be unaware of their eligibility for refunds in specific scenarios, such as delays exceeding a certain threshold.
- Operational Bottlenecks: Manual processing of refunds can lead to delays, further frustrating passengers.

Addressing these challenges can not only improve the passenger experience but also provide valuable feedback for operational improvements.

IV. PREDICTIVE MODELING

4.1 Average Deviation by Time of Day

Efficient railway operations rely on maintaining punctual schedules. Analyzing average deviation patterns across different times of the day provides valuable insights into operational bottlenecks and passenger experiences.

1) Key Observations from fig 7:

- Peak Deviation at 10:00 AM:

  The largest deviation, approximately 20 minutes, occurs around 10:00 AM. This likely reflects mid-morning operational adjustments and cascading effects from earlier delays during the morning rush hour[11].

- Secondary Spike at 6:00 PM:

  A secondary increase in deviation occurs around 6:00 PM, aligning with evening rush hour, indicating operational congestion and high passenger volume.

- Stable Performance in Early Morning and Late Night:

  Minimal deviations are observed during off-peak hours (midnight to 6:00 AM and after 9:00 PM), likely due to fewer operational complexities and reduced traffic.

2) Implications for Railway Management:

- Proactive Scheduling:

  Implement strategies to minimize delays during peak deviation times by improving scheduling and real-time adjustments.

- Passenger Communication:

  Enhance real-time delay notifications for passengers traveling during high-deviation hours, ensuring transparency and reducing dissatisfaction.

- Future Optimization:

  Investigate external factors contributing to these spikes, such as weather, infrastructure maintenance, and staffing during peak hours.

3) Actionable Recommendations:

- Introduce targeted solutions for peak times, such as additional resources or revised train schedules during mid-morning and evening rush hours.
- Optimize maintenance schedules to avoid overlaps with high-traffic periods.

4.2 Predicting Actual Arrival Times

Accurate prediction of actual arrival times is critical for improving passenger trust and operational planning. By leveraging the dataset and employing a Random Forest Regression model, we developed a predictive framework for forecasting arrival times.

1. Model Performance:

   - Evaluation Metrics:

   The model achieved a Mean Absolute Error (MAE) of approximately 5 minutes and a Root Mean Squared Error (RMSE) of 7 minutes, demonstrating high accuracy.

   - Predicted vs. Actual Arrival Times:

   The fig 8, shows that predicted values align closely with actual arrival times. Deviations are limited to outliers, which occur primarily during significant delays caused by unforeseen circumstances.

2. Operational Insights:

   - Morning and Evening Rush Hours:

   Higher deviations during these times underline the need for dynamic scheduling and real-time monitoring to mitigate cascading effects. Real-time delay notifications significantly enhance passenger satisfaction [12].

   - Predictive Accuracy:

   The model's high accuracy demonstrates its potential for real-world applications, such as enhancing delay notifications and optimizing crew schedules.

3. Future Enhancements:

   - Incorporate external factors (e.g., weather, infrastructure conditions) into the predictive framework for even greater accuracy.

By analyzing average deviations and actual arrival time predictions, this study provides actionable insights for improving railway operations, minimizing delays, and enhancing passenger satisfaction. These findings underscore the importance of data-driven decision-making in optimizing transportation systems.

V. Conclusion

This study provides a comprehensive analysis of railway operations, focusing on factors such as refund requests, journey deviations, and arrival time predictions. By leveraging a dataset with over 31,000 records, the research highlights critical trends in customer behavior, operational efficiency, and predictive modeling.

Through the use of UK railway ticketing data, this research has given way to actionable insights pertaining to customer behaviour, revenue generation, and operational efficiency. We analyzed trends across ticket types, classes, and railcard usage to identify key factors influencing revenue, such as the dominance of certain ticket types like Advance and Anytime in specific travel periods. Lastly, delay prediction using Random Forest models has shown the potential of data-driven solutions for solving one of the most topical challenges in railway operations: on-time performance.

Results show also the trend of customer preference in which pattern in types of ticket usage and request for refunds create an opportunity for focused interventions in order to increase customer satisfaction. Even though this data set only covered a period of four months, this clearly illustrates the potential for advanced analytics to drive decision-making in the railway industry.

This sets a strong foundation for further studies that will include real-time data and advanced techniques of machine learning. Findings from this research can be integrated into railway operations in a manner that will significantly improve customers' experiences, optimize resources, and increase general efficiency within the UK's railway network.

Key Findings:

- Refund Trends:

  Refund requests were underutilized, with only 27% of transactions involving claims, where the journey is delayed or cancelled.

  This highlights a gap in passenger awareness or accessibility to refund processes. Most refund claims were made for cancelled journeys (30%), while only 24% were made for delayed journeys.

- Journey Deviations:

  Significant deviations were observed during peak periods, particularly at 10:00 AM and 6:00 PM, indicating operational bottlenecks.

  Early morning and late-night journeys showed minimal deviations, reflecting lower congestion during off-peak hours.

- Predictive Accuracy:

  The Random Forest Regression model achieved high accuracy in predicting arrival times, with a Mean Absolute Error (MAE) of 5 minutes.

  The scatterplot of predicted vs. actual times demonstrated strong alignment, except for a few outliers caused by extreme delays.

Practical Implications:

This study underscores the importance of data-driven decision-making in railway operations. By addressing gaps in refund processes, optimizing schedules for peak periods, and leveraging predictive models, railway operators can enhance customer satisfaction and operational efficiency.

The findings pave the way for further exploration of predictive analytics and customer-centric solutions, offering valuable insights for the future of railway systems.

VI. Limitations and Future Work

6.1 Limitations of the Study

While this study provides valuable insights into railway operations, there are certain limitations that need to be addressed:

- Model Scope:

  The predictive model focused primarily on actual arrival times. Other aspects, such as delay root cause analysis or dynamic pricing predictions, were not explored.

External validation was not performed due to the lack of external datasets, potentially limiting the generalizability of the results.

- Passenger-Centric Insights:

While the analysis considered refund requests and customer behavior, qualitative insights from passenger feedback or sentiment analysis were not integrated.

- Operational Factors:

  The study did not consider real-time railway operation factors such as crew scheduling, train capacity, or route traffic, which could enhance the practical applicability of the recommendations.

- Feature Limitations:

  Key factors influencing railway operations, such as weather conditions or major events, were not included in the dataset, potentially limiting the accuracy of delay predictions.

- Model Limitations:

  Although Random Forest performed well in predicting delays, more advanced techniques (e.g., neural networks) were not explored due to computational constraints and the need for deeper domain knowledge.

6.2 Future Work

To address these limitations and expand the scope of the study, future research could explore the following areas:

- Integration of External Factors:

Integrate real-time operational data, such as live train tracking, weather patterns, infrastructure conditions, and event schedules, into predictive models to improve accuracy and applicability to power its capabilities in making delay predictions and maximizing revenues.

- Enhanced Predictive Modeling:

Consider more complex machine learning algorithms like Gradient Boosting Machines (GBM) for example XGBoost, Neural Networks, Reinforcement Learning or deep learning methods to capture complex patterns in the data and improve predictions.

Extend the model to predict other metrics, such as delay duration.

- Real-Time Analytics:

Develop real-time delay prediction systems that provide actionable insights to railway operators and passengers.

- Passenger Sentiment Analysis:

Include customer feedback data in order to understand passenger satisfaction in detail and identify service improvement opportunities

- Collaboration with Railway Operators:

Work closely with railway companies to obtain enriched datasets and test the predictive models in real-world scenarios.

- Long-term revenue optimization:

Design a recommendation system to suggest optimal travel time or ticket type for the customer based on historical data.

Consider the impact that promotional campaigns or discounts have on ticket sales and consumer loyalty.

Develop passenger-facing tools, such as mobile apps for real-time updates and simplified refund processes.

- Broader Applications:

Apply the methodology to other transportation systems, such as metro or bus networks, to evaluate its adaptability and impact.

- Scalability and Real-World Testing:

Testing the models with large real-world data from many years. For model improvement or validation. Liaise with railway operators to establish pilot demonstrations for delay prediction or revenue optimization.

VII. Refernces

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