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A SYSTEMATIC LITERATURE REVIEW OF LEVERAGING ARTIFICIAL INTELLIGENCE FOR DEMAND FORECASTING IN THE CAR RENTAL INDUSTRY OVER THE LAST DECADE

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A Systematic Literature Review of Leveraging Artificial Intelligence for Demand Forecasting in the Car Rental Industry Over the Last Decade

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Abstract

The car rental industry, integral to global travel and transportation, has seen substantial evolution over the past decade, spurred by technological advancements and changing consumer expectations. Central to this industry's operational efficiency is the ability to accurately forecast demand, which informs fleet management, pricing strategies, and customer service. Traditional demand forecasting methods have often failed to address the complexity of market dynamics. However, the advent of data analytics and sophisticated techniques in artificial intelligence have introduced more precise predictive capabilities.
This study conducts a systematic review of the literature from the past ten years to assess the application of Intelligent models in demand forecasting within the car rental industry. Using databases like Scopus and IEEE Xplore, a total of 254 studies were initially identified, with 11 meeting the inclusion criteria for in-depth analysis. The review examines various Intelligent techniques, their effectiveness, and the impact of different data types on model performance. The findings highlight common methodologies, key predictive factors, and performance metrics, such as Mean Absolute Error and Root Mean Squared Error. Models like Convolutional Neural Networks, and ensemble methods demonstrated superior accuracy.
Despite these advancements, challenges remain, including data redundancy, computational complexity, and the need for extensive feature engineering. This study provides a comprehensive synthesis of current approaches, identifies gaps like the lack of interpretability of existing models, and suggests future research directions to enhance demand forecasting accuracy and operational efficiency in the car rental sector.

Keywords: Car rental industry, Demand forecasting, Pricing strategies, Machine Learning, Artificial intelligence

1. Introduction

The inception of the industry is often attributed to Joe Saunders of Omaha, Nebraska, who, in 1916, started renting out a Model T Ford to local and visiting businessmen [1], [2]. The car rental industry, a pivotal component of the global travel and transportation sector, has undergone significant transformations over the past decade [3], driven by advancements in technology and shifting consumer expectations [4]. Central to the operational efficiency and strategic decision-making in this industry is the ability to accurately forecast demand [5], [6]. Demand forecasting enables car rental companies to optimize fleet management, pricing strategies, and customer service, thereby improving profitability and customer satisfaction [7]. In this context, data analytics has emerged as a critical tool, providing deeper insights and predictive capabilities that were previously unattainable through traditional methods.

Historically [8], demand forecasting in the car rental industry relied heavily on heuristic approaches and basic statistical methods, which, while useful, often fell short of capturing the complexity and dynamism of market conditions [9]. The proliferation of big data and advancements in computational technologies have paved the way for more sophisticated analytical techniques [10], [11]. These include machine learning algorithms, time-series analysis, and artificial intelligence, which have the potential to revolutionize demand forecasting by offering more accurate and granular predictions [12], [13].

The importance of demand forecasting cannot be overstated. Accurate demand predictions help car rental companies maintain an optimal fleet size [14], reducing excess inventory and vehicle shortage risk [15]. This balance is crucial for minimizing costs and maximizing revenue. Furthermore, effective demand forecasting supports better pricing strategies [14], [16], enabling companies to adjust prices dynamically based on predicted demand, competitor actions, and market conditions [17]. Such dynamic pricing can enhance competitive advantage and increase market share.

In recent years, the integration of data analytics into demand forecasting has been accelerated by several factors. The increasing availability of diverse data sources [18], such as online booking data, customer reviews, social media interactions, and economic indicators, provide a rich dataset for analysis [19], [20].

Despite the evident advantages of data analytics, there remains a lack of comprehensive synthesis regarding its application in demand forecasting specifically within the car rental sector. Existing studies like [21] often focus on narrow aspects or isolated case studies, without providing a holistic view of the advancements and their practical implications over the past decade. This gap underscores the need for a systematic review that collates and examines the various approaches, methodologies, and outcomes associated with the use of data analytics in this context.

The primary objective of this study is to systematically review the literature from the past ten years to understand how data analytics has been leveraged for demand forecasting in the car rental industry. By doing so, this research aims to identify the most effective techniques, highlight common challenges, and suggest future directions for both practitioners and researchers. Through a detailed analysis of existing literature, this study offers valuable insights into the current state of the field and the potential for future advancements.

2. Rationale

The car rental industry operates in a highly competitive and dynamic market, where effective demand forecasting is critical for optimizing fleet management, pricing strategies, and overall operational efficiency [22], [23]. Over the past decade, advancements in data analytics have transformed numerous industries, providing new tools and methodologies for improving demand forecasting accuracy [24]. Despite the potential benefits, there is a lack of comprehensive understanding regarding the specific applications and impacts of data analytics in the context of car rental demand forecasting.

This study aims to fill this gap by conducting a systematic literature review of the recent advancements in data analytics as applied to demand forecasting within the car rental industry. By synthesizing research findings from the past ten years, this study provides insights into the methodologies employed, the challenges encountered, and the successes achieved in leveraging data analytics for predicting demand in this sector.

The rationale for this research is threefold. First, understanding the state-of-the-art techniques in demand forecasting can help car rental companies adopt the most effective strategies to enhance their competitiveness. Second, identifying the challenges and limitations faced in this area can guide future research and development efforts to address these issues. Lastly, by mapping out the evolution and trends in this field, this study offers a valuable resource for both academics and practitioners aiming to improve their demand forecasting capabilities through data analytics.
Ultimately, this research contributes to the existing body of knowledge by providing a thorough examination of how data analytics has been utilized for demand forecasting in the car rental industry, highlighting its potential and identifying avenues for future innovation.

3. Objectives

This study aims to systematically review and analyze the existing literature on the application of artificial intelligence (AI) and machine learning (ML) models for demand forecasting in the car rental industry over the past decade. The specific objectives are to:

1. analyze the various AI techniques for demand forecasting in the car rental industry in recent studies.
2. assess the effectiveness of current models in forecasting demand for car rental services.
3. examine the impact of different types of data and sources on the performance of the models.
4. synthesize best practices and common methodologies for training, validating, and testing Intelligent models.
5. identify gaps in the existing literature and suggest recommendations for future research directions.

4. Methodology

This research study was conducted in alignment with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to ensure comprehensive and transparent reporting [25], [26]. The search strategy involved querying two academic databases, which included Scopus and IEEE Xplore to identify relevant articles published between January 2014 and December 2024. The search terms included variations of “car rental,” “vehicle hire,” “car sharing,” “demand forecasting,” “artificial intelligence,” “machine learning,” and “deep learning.” Restrictions were placed on language, selecting only publications in the English language, and final publication articles were considered.

Scopus Database: The search query on the Scopus database returned 151 document results.
TITLE-ABS-KEY (("machine learning" OR "artificial intelligence" OR "Statistical learning" OR "Data-driven modeling" OR "Deep learning") AND ("Demand*" OR "Sales forecast*" OR "Sales predict*" OR "Sales project*" OR "Market demand forecast*" OR "Predictive*") AND ("car rental" OR "Vehicle rental" OR "Car hire" OR "Auto* rental" OR "Car leasing" OR "Vehicle leasing" OR "Car sharing" OR "Rent-a-car" OR "Fleet management" OR "Vehicle fleet rental" OR "Transportation rental" OR "Mobility service" OR "Vehicle hire")) AND (LIMIT-TO (PUBSTAGE,"final")) AND (LIMIT-TO (LANGUAGE,"English"))

IEEE Xplore Database: On the IEEE Xplore Database, the following Search Query returned 103 results.
(("Artificial Intelligence" OR "Machine Learning" OR "Deep Learning" OR "Neural Networks") AND ("Demand Forecasting" OR "Demand Prediction" OR "Demand Estimation" OR "Demand Modeling") AND ("Car Rental Industry" OR "Vehicle Hire" OR "Car Hire" OR "Rental Car Companies" OR "Vehicle Rental Services")) AND (Publication_Year:2014 TO 2024)
Specific criteria were developed to determine whether articles were suitable for inclusion in this review.

4.1. Exclusion Criteria

Publications that do not specifically address demand forecasting in the car rental industry using AI or ML models were excluded. Articles focusing on unrelated topics such as general car rental management, customer satisfaction, or fleet optimization without specific emphasis on demand forecasting were not considered. Additionally, publications not written in English or those published outside the last decade (2014 – 2024) were excluded. Studies lacking sufficient detail on the methodologies used for demand forecasting, making it impossible to evaluate their performance or limitations, were also excluded. Furthermore, studies with inadequate sample sizes or those demonstrating a high risk of bias, which could compromise the reliability and generalizability of their findings, were omitted from this review.

4.2. Eligibility Criteria

Participants: Studies involving car rental companies or datasets specifically focusing on demand forecasting in the car rental industry.
Interventions: Articles employing AI and statistical techniques for demand forecasting, including but not limited to supervised learning, unsupervised learning, and deep learning methods.
Comparisons: Comparisons across different demand forecasting models and their methodologies as reported in the identified studies.
Outcomes: Primary outcomes of interest include the accuracy, mean absolute error (MAE), root mean squared error (RMSE), and R-squared of the demand forecasting models.
Study Design: This systematic review includes studies that report the development and evaluation of Intelligent models for demand forecasting in the car rental industry. The studies are selected using the PRISMA guidelines.

4.3. Information Sources

Scopus and IEEE Xplore databases are used as the primary information sources. The last search date was June 17, 2024.

4.4. Study Selection

The screening exercise was conducted by a team of researchers. Titles and abstracts of the studies retrieved from the search were assessed for eligibility based on the predefined inclusion and exclusion criteria. Full-text articles were retrieved for all studies that meet the eligibility criteria.

4.5. Data Collection

Data were extracted from the included studies and combined into one CSV file using a standardized data extraction form. Data extraction was done by the researchers, and any discrepancies were resolved through the application of the eligibility criteria and personal judgment from combined team efforts. The extracted data included study characteristics, participants, interventions, outcomes, and results.

4.6. Data Items

Study Characteristics: Title, author, year of publication, journal name, study design, sample size, inclusion and exclusion criteria, and data sources.
AI Model Characteristics: Model type, algorithm, feature selection, data preprocessing, model validation, performance metrics, and limitations.
Demand Forecasting: Forecasting accuracy, mean absolute error (MAE), root mean squared error (RMSE), and R-squared.
Study Outcomes: Reported performance of the AI models for demand forecasting, as well as any limitations and future research directions.
Funding Sources: Any funding sources related to the development or evaluation of the AI models.
Conflicts of Interest: Any conflicts of interest related to the authors, funders, or institutions involved in the study.

4.7. Risk of Bias Assessment

The risk of bias assessment was performed independently by the researcher using the eligibility criteria. This includes:
Selection Bias: Adequate randomization or allocation concealment, and clear definition and consistent application of inclusion and exclusion criteria.
Performance Bias: Equal treatment of intervention and control groups in terms of administration of the AI model and standardization of care.
Detection Bias: Blinding of outcome assessors to the intervention and control groups.
Attrition Bias: Reporting and accounting for significant loss to follow-up.
Reporting Bias: Assessment of selective reporting of outcomes or other types of bias affecting the validity of the study results.
The risk of bias assessment would guide the interpretation and synthesis of the study results. Studies with a high risk of bias may be excluded from the final review.

4.8. Summary Measures

The principal summary measures are be odds ratios (OR) or hazard ratios (HR) with 95% confidence intervals (CI) for the classification accuracy of the AI models.

4.9. Synthesis of Results

A narrative synthesis was performed, with the findings of the included studies summarized and presented in tabular form. If there are sufficient studies, a meta-analysis was performed using a random-effects model. Heterogeneity was assessed using the I^2 statistic.

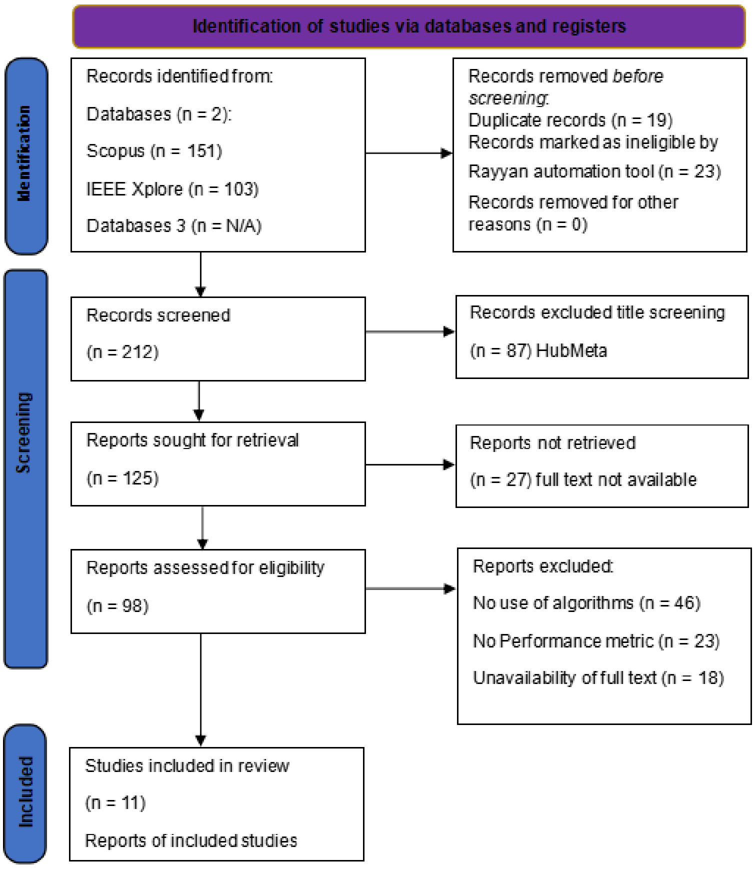

Figure 1: The Flow diagram shows the study eventually screened

5. Results

254 studies were initially identified from the Scopus and IEEE Xplore databases. Following the application of exclusion criteria, 212 studies were excluded, leaving 42 studies for full-text review. After further assessment, 11 studies met the eligibility criteria and were included in this systematic review. Table 1 displays the models used, performance metrics scores, data type, key predictive factors, and limitations of the reviewed studies. Table 2 focuses on the popular performance metrics which include MAE, RMSE, and MAPE for every existing model reviewed. These studies encompass a variety of predictive models, algorithms, and methodologies employed in demand forecasting for the car rental industry over the last decade. The studies identified a diverse array of key predictive factors influencing demand forecasting. Common factors included historical sales data, calendar data (including holidays and promotional periods), real-time booking data, customer demographics, and economic indicators.

Table 1: Summary of the Reviewed Studies

Author(s) (Year)	César et al, (2023) [27]
Data Type	Multivariate time series data (Temporal, Meteorological, User Behavior Variables, and Event-related)
Model(s)	Linear Regression (LR), Polynomial Regression (PR), Lasso Regression, Ridge Regression, Support Vector Regression (SVR), Random Forest (RF), Multilayer Perceptron (MLP), Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), Extreme Learning Machine (ELM)
Performance Metrics	R-squared (R^2), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE). CNN performed best.
Limitation(s)	Large numbers of predictor variables could cause redundancy or multi-collinearity issues. Linear models (LR, PR, Lasso) showed poor RMSE scores, suggesting sensitivity to severe outliers, some complex models (like MLP, LSTM, GRU) may not need extensive feature engineering, but simpler models could benefit significantly from it.
Author(s) (Year)	Dong et al, (2017) [28]
Data Type	Categorical and numerical data (AreaID, TimeID, WeekID, Weather Conditions)
Model(s)	Empirical Average, Gradient Boosting Decision Tree (GBDT), LASSO (Least Absolute Shrinkage and Selection Operator), Random Forest (RF), Basic DeepSD, and Advanced DeepSD
Performance Metrics	Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). Advanced DeepSD performed best.
Limitation(s)	Measures such as dropout were used to prevent overfitting, indicating this is a concern in model training. The advanced deep learning models which might require significant computational resources and optimization efforts are complexity concerns.
Author(s) (Year)	Yuming et al, (2020) [29]
Data Type	Large-scale travel data including temporal, spatial, and weather characteristics.
Model(s)	Random Forest (RT), LightGBM (Light Gradient Boosting Machine), Support Vector Regression (SVR), Long Short-Term Memory (LSTM), Stacking Ensemble Learning Model.
Performance Metrics	Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE). Stacking Ensemble Learning Model performed best.
Limitation(s)	Previous studies largely focused on historical data mining from temporal and spatial features separately, but a combined spatiotemporal approach is often overlooked.
Author(s) (Year)	Man et al, (2019) [30]
Data Type	Large-scale datasets (Temporal features, Spatial features, External factors), specifically the car-hailing order data aggregated at different time intervals (10 min, 15 min, and 30 min).
Model(s)	Random Forest (RF), Support Vector Regression (SVR), LightGBM, Long Short-Term Memory (LSTM), Stacking Ensemble Learning Model

Performance Metrics	Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE). Stacking Ensemble Learning Model performed best.
Limitation(s)	Data aggregated at shorter time intervals have greater data noises and more useless fluctuation information, making them more difficult to predict accurately.
Author(s) (Year)	Erika et al, (2023) [31]
Data Type	Historical data consisting of 17,650 rows representing carsharing reservations (Age of customers, Traveling patterns, Reservation patterns).
Model(s)	Holt-Winters (HW), Auto-Regressive Integrated Moving Average (ARIMA)
Performance Metrics	Mean Absolute Error (MAE), Mean Squared Error (MSE), Mean Absolute Percentage Error (MAPE). HW performed better.
Limitation(s)	There might be an inherent limitation in using only historical data without integrating real-time data, which could affect the accuracy and responsiveness of the predictive models.
Author(s) (Year)	Nihad et al, (2021) [32]
Data Type	Time series data related to car-sharing transactions, environmental conditions, and temporal information.
Model(s)	eXtreme Gradient Boosting (XGBoost), Vector Autoregression (VAR), Support Vector Regression (SVR), K-Nearest Neighbors (KNN), Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), Convolutional Neural Network (CNN), CNN-LSTM (hybrid model), Multilayer Perceptron Regressor (MLP)
Performance Metrics	Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), Root Mean Squared Logarithmic Error (RMSLE)
Limitation(s)	Limited to temporal features and did not incorporate a broader range of potentially influential variables such as Period of data, Spatiotemporal variables, and Consumer habits.
Author(s) (Year)	Yuhan et al, (2021) [33]
Data Type	Time series data of car-sharing transactions (Past Usage, Temporal Information, Environmental Conditions)
Model(s)	Vector Autoregression (VAR), eXtreme Gradient Boosting (XGBoost), Support Vector Regression (SVR), K-Nearest Neighbors (KNN), Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), Convolutional Neural Network (CNN), Multilayer Perceptron (MLP), Hybrid model (CNN-LSTM)
Performance Metrics	Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), Root Mean Squared Logarithmic Error (RMSLE). The CNN-LSTM hybrid model performed best.
Limitation(s)	Temporal features suggest future studies could expand by including more features such as spatiotemporal variables and consumer habits. Deep learning models, especially the hybrid CNN-LSTM, have high complexity and require significant computational time compared to other models.
Author(s) (Year)	Michele et al, (2020) [34]

Data Type	Time series data of car-sharing usage (Time of Day, Day of the Week, Weather Conditions).
Model(s)	ARIMA, SARIMA, Linear Regression, Support Vector Regression (SVR), Long Short-Term Memory (LSTM), Random Forests Regression, Neural Network Model
Performance Metrics	Mean Absolute Percentage Error (MAPE), Absolute Percentage Error (APE), Root Mean Squared Error (RMSE). Random Forests Regression performed best.
Limitation(s)	The study did not use weather information for long-term predictions due to the difficulty of accurately forecasting weather far in the future and there is a lack of interpretability.
Author(s) (Year)	Elena et al, (2020) [35]
Data Type	Time series data of car occupancy levels in urban areas (Time of Day, Day of the Week, Weather Conditions, Spatial Context, Functional Context).
Model(s)	Random Forest (RF), Gradient Boosting Tree (GBT), Lasso, Linear Regression (LR)
Performance Metrics	Mean Absolute Error (MAE). LR performed best.
Limitation(s)	Lack of interpretable models, which could provide insights into the most important features for the prediction problem. The study did not use weather information for long-term predictions due to the difficulty of accurately forecasting weather far in the future.
Author(s) (Year)	Peerapon et al, (2021) [36]
Data Type	Vehicle usage logs (Historical sales volume data)
Model(s)	BiGRU (Bidirectional Gated Recurrent Unit), GRU (Gated Recurrent Unit), LSTM (Long Short-Term Memory)
Performance Metrics	Root Mean Square Error (RMSE). BiGRU performed best.
Limitation(s)	The study did not consider any external factors or variables beyond the historical sales data, such as weather, economic conditions, or other market factors that could influence demand. The study focused on short-term (3 week) demand forecasting and did not explore longer-term forecasting horizons.
Author(s) (Year)	Alireza et al, (2020) [37]
Data Type	Ride requests from TAP30 corporation (Day of week, National holiday, Time slot, Spatial Features)
Model(s)	Simple Recurrent Neural Network (RNN), Gated Recurrent Unit (GRU), Long Short-Term Memory (LSTM), eXtreme Gradient Boosting (XGBoost), Least Absolute Shrinkage and Selection Operator (LASSO), Auto Regression Integrated Moving Average (ARIMA)
Performance Metrics	Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE). GRU performed best.
Limitation(s)	The study focused on short-term demand forecasting and did not explore longer-term forecasting horizons. The sample size was relatively small, with only 256 regions and 15-minute time intervals over 4 months.

Table 2: Popular Performance Metrics Score for Existing Model

Model	**MAE**	**RMSE**	**MAPE**
LR [27]	149.06	182.63	73.87
RT [29]	59.03	85.58	37.56
RF [28]	43.49	66.58	26.75
Lasso [27]	114.98	141.03	63.25
MLP [27]	110.79	145.06	49.93
SVR [29]	161.94	197.75	280.22
ELM [27]	361.51	619.72	373.83
LSTM [32]	100.45	140.69	53.33
RNN [37]	79.18	114.72	68.44
GRU [32]	67.94	107.01	38.10
CNN [33]	40.08	58.15	26.23
DeepSD [28]	33.02	140.14	36.74
Holt-Winters [31]	27.08	12.43	13.12
ARIMA [34]	34.00	20.16	18.23
XGBoost [32]	16.91	46.36	57.42
VAR [33]	84.65	291.34	139.18
KNN [32]	272.81	165.39	194.87
CNN-LSTM [33]	27.85	40.46	109.23
GBDT [28]	60.25	89.93	55.65
GBT [35]	46.95	59.79	53.88
LightGBM [30]	46.26	47.42	57.76
RR [27]	39.78	40.54	51.23
SARIMA [34]	20.01	160.42	17.60

6. Findings

From the comprehensive review of 254 studies, 11 met the inclusion criteria and were included in this systematic literature review. The findings from these studies reveal a diverse range of AI and machine learning models utilized for demand forecasting in the car rental industry, each with varying levels of success and limitations. The key models identified include Linear Regression (LR), Polynomial Regression (PR), Lasso Regression, Ridge Regression, Support Vector Regression (SVR), Random Forest (RF), Multilayer Perceptron (MLP), Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), and Extreme Learning Machine (ELM). The findings include the following:

a) *Performance Metrics*: The performance of these models was primarily evaluated using metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and R-squared (R^2). Among the models, CNN, advanced deep learning models like CNN-LSTM hybrids, and stacking ensemble learning models consistently showed superior performance in terms of forecasting accuracy.
b) *Data Types and Sources*: The studies utilized various types of data, including multivariate time series data, historical sales data, temporal and spatial data, weather conditions, and

customer demographics. The integration of diverse data sources was found to enhance the predictive accuracy of the models.

c) *Model Effectiveness*: Models like CNN and LSTM showed robust performance due to their ability to capture complex patterns and dependencies in the data. However, simpler models like Linear Regression and Lasso Regression often struggled with large datasets and were sensitive to outliers.

d) *Challenges and Limitations*: Common challenges identified include overfitting, especially in complex models, computational resource requirements, and the need for extensive feature engineering. Additionally, many studies highlighted the limitations of using historical data without real-time data integration, which can affect the responsiveness and accuracy of demand forecasts.

e) *Best Practices*: The review identified best practices such as using ensemble learning techniques, incorporating both temporal and spatial features, and applying regularization methods to prevent overfitting. The importance of model validation and cross-validation to ensure the reliability of the forecasting models was also emphasized.

7. Discussion

The findings from this systematic literature review underscore the significant advancements in leveraging AI and machine learning for demand forecasting in the car rental industry. Over the past decade, there has been a noticeable shift from traditional statistical methods to more sophisticated AI-driven approaches which include data preprocessing and exploratory data analysis, reflecting broader trends in the adoption of data analytics across various industries. The various trends are discussed below:

a) *Technological Evolution*: The evolution from heuristic methods to advanced machine learning models highlights the industry's response to increasing data availability and computational power [38], [14]. Machine learning models, particularly deep learning models, have demonstrated a substantial improvement in forecast accuracy, which is critical for operational efficiency in the car rental industry.

b) *Data Integration*: The integration of diverse data sources, including real-time booking data and external factors like weather and economic indicators, has proven beneficial. This comprehensive data integration allows models to capture more nuanced demand patterns, leading to more accurate and actionable forecasts [39], [40].

c) *Model Performance*: While advanced models like CNNs and LSTMs offer superior performance, their complexity and resource requirements pose significant challenges. These models require large datasets and substantial computational power, which may not be feasible for all car rental companies, especially smaller ones.

d) *Practical Implications*: For car rental companies, adopting AI-driven demand forecasting models can lead to better fleet management, optimized pricing strategies, and improved customer satisfaction [41]. However, the practical implementation of these models requires careful consideration of the company's data infrastructure, computational resources, and expertise in AI and machine learning.

e) *Future Directions*: The review identifies several areas for future research. These include developing more interpretable models, exploring the use of real-time data, and investigating the impact of emerging technologies such as the Internet of Things (IoT) and blockchain on demand forecasting. Additionally, there is a need for more studies that focus on the practical implementation and scalability of these models in real-world settings.

8. Conclusion

This study provides a comprehensive overview of the advancements in AI and machine learning for demand forecasting in the car rental industry over the past decade. The findings indicate that while significant progress has been made, there are still several challenges to be addressed. Advanced models like CNNs and LSTMs offer promising results but come with higher complexity and resource requirements. The integration of diverse data sources has been beneficial, yet real-time data utilization remains underexplored. For practitioners, this review highlights the importance of adopting a data-driven approach to demand forecasting, leveraging the most effective AI techniques, and considering the practical implications of model implementation. For researchers, it points to the need for developing more interpretable and scalable models and exploring new data sources and technologies. Leveraging AI for demand forecasting holds great potential for the car rental industry, offering the promise of more accurate predictions and optimized operations. However, realizing this potential requires ongoing research, technological innovation, and practical adaptation to the unique challenges of the industry.

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