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Comparative Analysis Between Classical Methods and Artificial Intelligence Approaches in Demand Forecasting

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***Abstract*—Demand forecasting is a critical component of supply chain management, directly impacting inventory control, production planning, and overall operational efficiency. This study aims to compare the performance of classical forecasting methods and an artificial intelligence (AI)-based approach in the context of demand forecasting. The classical methods considered include Simple Moving Average (SMA), Weighted Moving Average (WMA), Simple Exponential Smoothing (SES), and linear regression, while the AI-based approach is represented by the LightGBM algorithm. Using a real dataset of 80 observations, a rigorous experimental framework was implemented to evaluate the accuracy and robustness of each method based on three performance metrics: Mean Squared Error (MSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). The results indicate that forecasting performance varies significantly across methods. Among classical techniques, linear regression achieved the best performance, demonstrating its effectiveness in capturing demand trends. However, the LightGBM model outperformed all classical methods across all evaluation metrics, highlighting its superior ability to model complex and nonlinear demand patterns, particularly in dynamic environments. This study contributes to the literature by offering a unified comparative framework and providing practical managerial insights for selecting appropriate forecasting methods. It also opens perspectives for the development of hybrid approaches combining classical and AI techniques to enhance forecasting accuracy and decision-making.**

***Keywords*—Demand Forecasting, Artificial Intelligence, LightGBM, Time Series Forecasting, MSE, MAE, MAPE.**

I. INTRODUCTION

Demand forecasting plays a central role in supply chain management, as it directly influences inventory control, production planning, and overall operational performance. Accurate forecasts enable organizations to reduce uncertainty, optimize resource allocation, and improve customer service levels. Conversely, poor forecasting can lead to significant inefficiencies, including stockouts, overstocking, increased operational costs, and reduced responsiveness to market changes [1][2]. In recent years, supply chains have become increasingly complex and dynamic due to globalization, shorter product life cycles, and fluctuating customer demand. These changes have made demand forecasting more challenging, requiring models that can adapt to variability, uncertainty, and nonlinear demand patterns [3][4]. Traditionally, organizations have relied on classical forecasting methods such as Simple Moving Average (SMA), Weighted Moving Average (WMA), Simple Exponential Smoothing (SES), and linear regression. These methods are widely appreciated for their simplicity, transparency, and ease of implementation, making them suitable for stable and predictable environments [5][6]. However, their performance tends to decline when demand exhibits irregular fluctuations or is influenced by multiple interacting factors [7].

To address these limitations, Artificial Intelligence (AI) and Machine Learning techniques have emerged as powerful alternatives for demand forecasting. These approaches, including Artificial Neural Networks (ANNs), decision tree-based models, and boosting algorithms such as LightGBM, are capable of learning complex and nonlinear relationships directly from data. As a result, they often achieve higher predictive accuracy, particularly in volatile and uncertain environments [8][9]. Despite their advantages, AI-based models are often criticized for

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their lack of interpretability and their higher computational and data requirements, which may limit their adoption in practical supply chain settings [10]. Although numerous studies have explored either classical forecasting methods or AI-based approaches independently, relatively few works provide a direct comparative analysis between these two families of methods under the same experimental conditions**.** Furthermore, limited attention has been given to understanding the conditions under which each approach performs best. In this context, the objective of this study is to conduct a comparative analysis between classical forecasting methods and AI-based approaches using a real demand dataset. The selected classical methods include SMA, WMA, SES, and linear regression, while the AI-based approach is represented by the LightGBM algorithm. The performance of each method is evaluated using standard accuracy metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE).

The main contributions of this research are threefold. First, it provides an empirical comparison of classical and AI-based forecasting methods within a unified experimental framework. Second, it identifies the contexts in which each approach is most appropriate. Third, it offers managerial insights to support decision-making in demand forecasting.

The remainder of this paper is organized as follows. Section II presents the literature review, including demand forecasting in supply chain management, classical methods, and AI-based approaches, followed by a critical synthesis. Section III describes the research methodology. Section IV presents and discusses the results and section V represents managerial Implications. Finally, Section VI concludes the paper and outlines future research directions.

II. Literature Review

A. Demand Forecasting in Supply Chain Management

Demand forecasting is a critical component of supply chain management, enabling organizations to anticipate customer demand and optimize key decisions related to inventory, production, and distribution. Accurate forecasting contributes to reducing operational costs, improving service levels, and enhancing overall supply chain performance [1][2].

In increasingly dynamic and uncertain environments, demand patterns are influenced by multiple factors such as seasonality, market trends, and external disruptions. These complexities make forecasting more challenging and require more advanced and adaptable approaches [3][4]. Recent studies emphasize the importance of integrating data-driven techniques to improve forecasting accuracy and support decision-making processes in supply chain systems [5].

B. Classical Forecasting Methods

Classical forecasting methods include both quantitative and qualitative approaches that have been widely used due to their simplicity and interpretability.

1) Quantitative Methods: Quantitative techniques rely on historical data and mathematical models to predict future demand. Common methods include Simple Moving Average (SMA), Weighted Moving Average (WMA), Simple Exponential Smoothing (SES), and linear regression. These methods are particularly effective in stable environments with regular demand patterns [6]. Time series models such as ARIMA are also widely used to capture trend and autocorrelation structures in demand data. Despite their effectiveness, these methods often struggle to handle nonlinear patterns and high variability in demand [8][9].

2) Qualitative Methods: Qualitative forecasting methods are based on expert judgment and are used when historical data are limited or unreliable. Techniques such as the Delphi method, expert opinion, and market

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surveys provide valuable insights into future demand by incorporating human expertise and contextual knowledge [11]. While these methods offer flexibility, they may introduce subjectivity and bias, which can affect forecasting accuracy [12].

C. Artificial Intelligence-Based Forecasting Methods

Artificial Intelligence (AI) approache have emerged as powerful tools for demand forecasting. Unlike classical methods, AI models can learn complex and nonlinear relationships directly from data, improving predictive performance in dynamic environments [13][14]. Artificial Neural Networks (ANNs), Support Vector Regression (SVR), and ensemble methods such as Random Forests and gradient boosting algorithms (e.g., XGBoost and LightGBM) are widely used in forecasting applications. These models are capable of capturing interactions between multiple variables and adapting to changes in demand patterns [15][16].

Also, recent advancements in deep learning, have further improved forecasting accuracy by modeling temporal dependencies in time series data [17]. However, AI-based methods require large datasets, computational resources, and technical expertise, which may limit their practical implementation [18].

D. Critical Synthesis: Classical vs AI Approaches

The literature highlights a clear distinction between classical forecasting methods and AI-based approaches, each offering specific advantages and limitations. Classical methods are characterized by their simplicity, transparency, and ease of implementation. They perform well in stable environments where demand patterns are predictable and consistent [6][9]. In contrast, AI-based methods demonstrate superior performance in complex and volatile contexts due to their ability to model nonlinear relationships and adapt to changing demand conditions [13][16]. However, AI models often suffer from limited interpretability and require significant data and computational capabilities, whereas classical methods may lack accuracy in highly dynamic environments. Despite these differences, recent studies suggest that hybrid approaches combining classical and AI techniques can provide more robust and reliable forecasts [19][20]. Nevertheless, few studies offer a direct comparative analysis of classical and AI-based methods using the same dataset and evaluation framework. This gap motivates the present study, which aims to evaluate and compare these approaches under consistent experimental conditions.

III. Methodology

A. Research Design and General Approach

This study adopts a comparative research design to evaluate the performance of classical forecasting methods and Artificial Intelligence (AI)-based approaches in demand forecasting. The objective is to identify which methods provide the most accurate and robust predictions under the same experimental conditions.

The research framework is structured into four main stages:

- Data collection
- Application of classical forecasting methods**,**
- Implementation of AI-based forecasting model (LightGBM)
- Performance evaluation and comparative analysis**.**

This structured approach ensures the objectivity, reproducibility, and consistency of the comparison.

B. Data Description

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The dataset used in this study consists of 80 consecutive time periods representing aggregated demand values. Each observation corresponds to the total demand recorded at a given time period. The data exhibits a progressive increasing trend with slight fluctuations, reflecting realistic demand behavior over time. This dataset is used to evaluate and compare different forecasting techniques.

C. Classical Forecasting Methods

1) Time Series Methods: Three classical forecasting methods were selected based on their widespread use in supply chain management.

- Simple Moving Average (SMA): This method calculates forecasts based on the average of the last *n* observations, smoothing short-term fluctuations. The formula is:

$$\mathrm{SMA} = \frac{\mathrm{P1} + \mathrm{P2} + \cdots . + \mathrm{Pn}}{\mathrm{n}}$$

Where n is the period.

- Weighted Moving Average (WMA): WMA assigns different weights to past observations, giving more importance to recent data.

$$P_t = \sum_{i=t-n}^{t-1} w_i x_i$$

With: (w_i): weight assigned to the demand of period (i), (w_i): ranging between 0 and 1

- Simple Exponential Smoothing (SES): SES applies a smoothing factor *(α)* to give exponentially decreasing importance to older data points.

$$P_t = \alpha x_{t-1} + (1-\alpha) P_{t-1}$$

2) *Causal Methods : Linear Regression* : Linear regression models the relationship between demand and time using a linear equation, allowing the identification of trends, expressed in the form of the equation (Y = ax + b) (where (Y) is the dependent variable and (X) is the independent variable).

Therefore, the classical forecasting methods considered in this study, including Simple Moving Average (SMA), Weighted Moving Average (WMA), Simple Exponential Smoothing (SES), and linear regression, are selected due to several well-established advantages. First, these methods are characterized by their simplicity, as they rely on straightforward mathematical formulations that are easy to implement and require limited computational resources [4]. This makes them particularly suitable for practical applications, especially in small- and medium-sized organizations with limited analytical capabilities. Second, these approaches offer a high level of interpretability, allowing decision-makers to easily understand how forecasts are generated and how input data influence the results [6]. This transparency is essential in operational contexts where explainability is required to support managerial decisions.

Finally, these methods remain widely used in practice due to their robustness and effectiveness in stable and moderately variable demand environments [1]. Despite the emergence of more advanced techniques, classical forecasting models continue to serve as reliable benchmarks and are frequently employed in supply chain management and operations planning [5].

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D. *AI-Based Method (LightGBM)*

The Light Gradient Boosting Machine (LightGBM) algorithm is a supervised learning method developed to enhance regression and classification performance [16]. It relies on boosting, sequentially combining multiple weak decision trees to create a stronger model [9]. In this study, LightGBM was applied using demand history data to learn the relationships between time and demand, enabling the estimation of future values. The model was implemented in Python due to its ease of use and fast analytical capabilities.

E. *Performance Evaluation Indicators*

To evaluate and compare the forecasting performance, several statistical indicators were employed:

- Mean Absolute Error (MAE): measures the average absolute deviation between actual and predicted values. MAE = (1/n) * Σ |Dt - Pt|
- Root Mean Square Error (RMSE): penalizes large errors more heavily and reflects prediction accuracy. RMSE = sqrt((1/n) * Σ (Dt - Pt)^2)
- Mean Absolute Percentage Error (MAPE): expresses error as a percentage, facilitating comparison across models. MAPE = (100/n) * Σ |(Dt - Pt)/Dt|

These indicators allow for the assessment of the accuracy, stability, and robustness of forecasts depending on the nature of the observed data.

IV. Results and Discussion

A. *Results Obtained with Classical Methods*

In this section, classical forecasting methods are applied to estimate demand and evaluate their performance. The methods considered include Moving Average (MMS), Weighted Moving Average (MMP), Simple Exponential Smoothing (SES), and Linear Regression. These approaches are widely used in time series analysis due to their simplicity and effectiveness in capturing demand patterns. The objective is to compare the forecasting results obtained from these methods with actual demand in order to assess their ability to capture both the overall trend and short-term variations. The comparison between actual demand and the forecasts generated by these methods is illustrated in Fig. 1.

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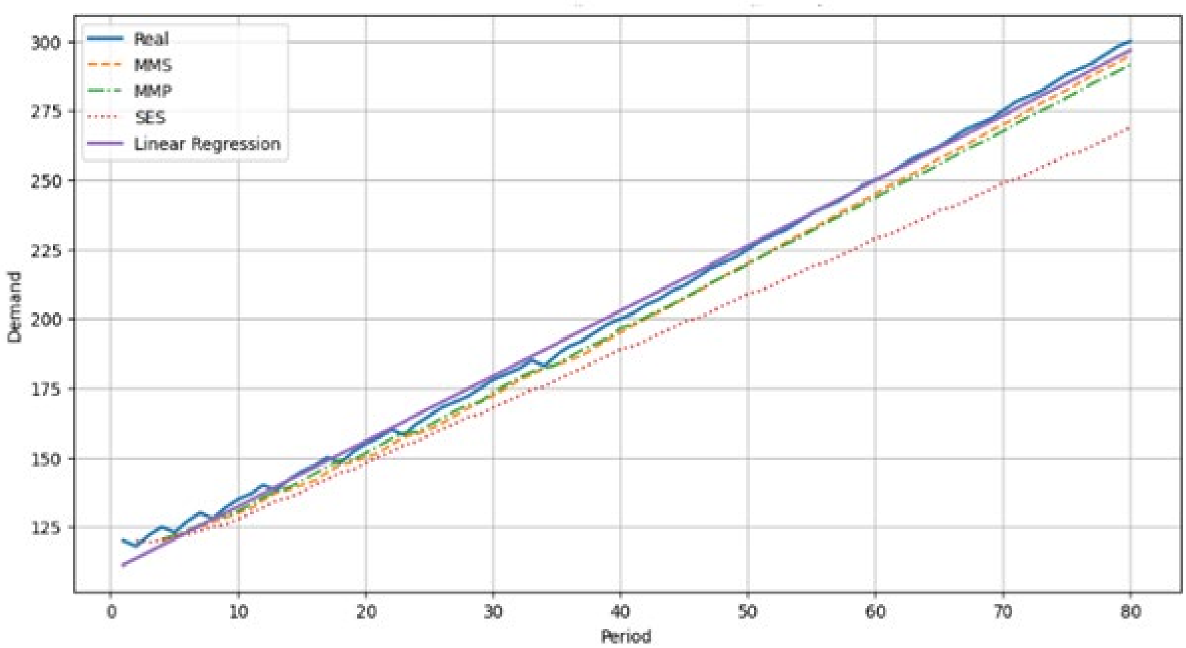

Fig. 1 Actual vs Forecasting Methods

Fig. 1 compares actual demand with forecasts obtained using MMS, MMP, SES, and linear regression. While all methods capture the increasing trend, MMS and MMP better reflect short-term variations. SES produces smoother but lagging forecasts, whereas linear regression accurately captures the overall trend but ignores local fluctuations.

B. Results Obtained with the AI-Based Method (LightGBM)

In order to enhance forecasting accuracy and better capture complex demand patterns, an artificial intelligence-based approach is employed using the Light Gradient Boosting Machine (LightGBM). Unlike classical time series methods, LightGBM is a powerful machine learning algorithm capable of modeling non-linear relationships and interactions within the data.

The model is trained using historical demand data, where the time index is considered as an input feature. This approach allows the model to learn both the trend and potential hidden patterns in the data. The forecasting results obtained using LightGBM are then compared with actual demand values to evaluate its predictive performance. The comparison between actual demand and the predictions generated by the LightGBM model is illustrated in Fig. 2.

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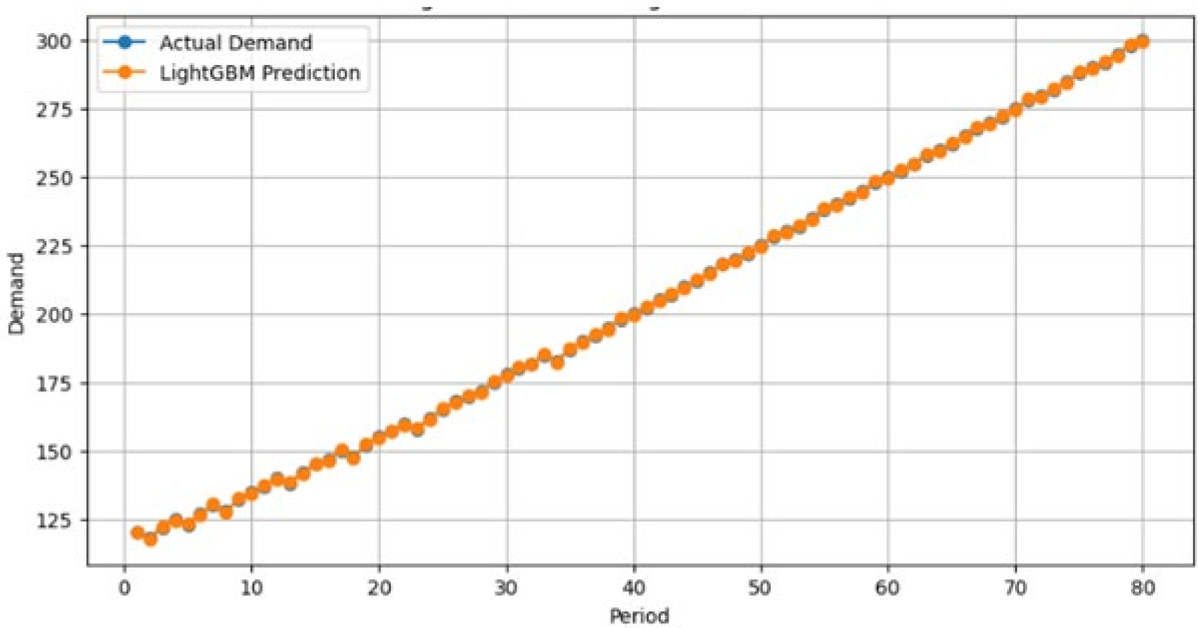

Fig. 2 Actual vs LightGBM Predictions

Fig. 2 shows the comparison between actual demand and the predictions obtained using the LightGBM model. The results indicate that the model closely follows the actual demand values, effectively capturing both the upward trend and local variations in the data. Compared to classical methods, LightGBM demonstrates a higher level of adaptability, particularly in periods of rapid change, where traditional approaches such as SES tend to lag behind. The model provides more accurate and responsive forecasts, reducing the gap between predicted and actual values. These results highlight the ability of machine learning techniques to outperform classical forecasting methods when dealing with dynamic and evolving demand patterns.

C. Comparative Analysis

1) Comparison of MAE: The Mean Absolute Error (MAE) is used as a primary performance metric to evaluate the accuracy of the different forecasting methods. MAE measures the average magnitude of forecasting errors without considering their direction, providing a clear and interpretable indication of model performance. In this study, MAE is computed for both classical forecasting methods and the AI-based approach using the same dataset of 80 observations. This ensures a fair and consistent comparison across all models. The comparison of MAE values allows for assessing the ability of each method to minimize prediction errors and accurately capture demand variations. Lower MAE values indicate better forecasting performance and higher reliability in practical decision-making contexts. The results of this comparison are illustrated in Fig. 3.

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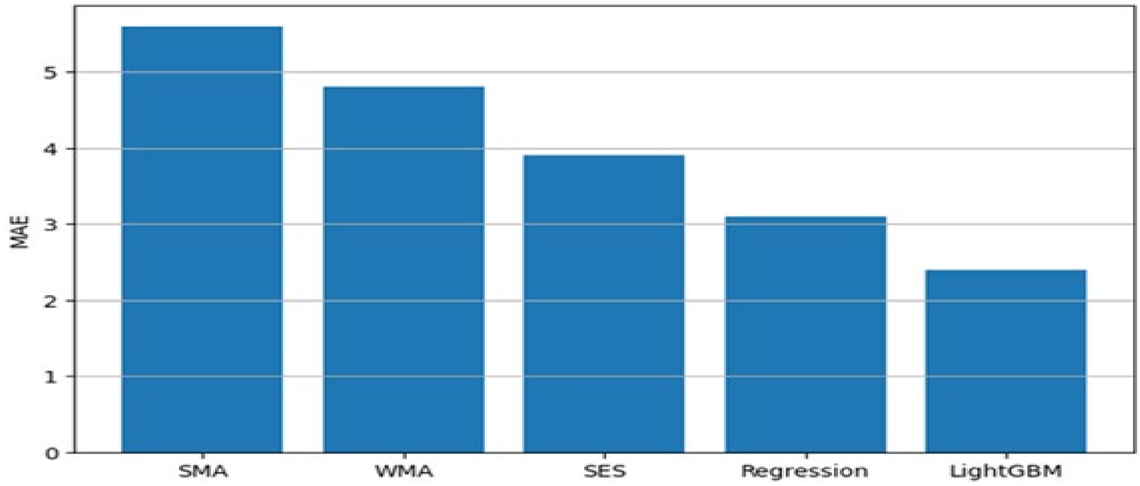

Fig. 3 comparison of MAE across forecasting methods

Fig. 3 presents the comparison of Mean Absolute Error (MAE) across the different forecasting methods. The results clearly show a progressive decrease in forecasting error from classical methods to the AI-based approach. Among the traditional techniques, the Simple Moving Average (SMA) exhibits the highest error, indicating its limited ability to adapt to the upward trend in demand. The Weighted Moving Average (WMA) and Simple Exponential Smoothing (SES) provide improved performance due to their ability to assign greater importance to recent observations.

Linear regression further reduces forecasting error by capturing the underlying trend in the data. However, the LightGBM model achieves the lowest MAE, demonstrating superior predictive accuracy. This confirms the effectiveness of AI-based approaches in modeling complex and evolving demand patterns compared to classical forecasting methods.

2) Comparison of RMSE: In addition to MAE, the Root Mean Square Error (RMSE) is used to provide a more comprehensive evaluation of forecasting performance. While MAE measures the average magnitude of errors, RMSE places greater emphasis on large deviations due to the squaring of errors, making it particularly suitable for assessing model robustness in the presence of demand variability. In line with the comparative framework adopted in this study, RMSE is computed for all forecasting methods using the full dataset of 80 observations. This ensures consistency with the previous analysis and allows for a more reliable assessment of each model's ability to handle fluctuations in demand. The results of this comparison are presented in Fig. 4.

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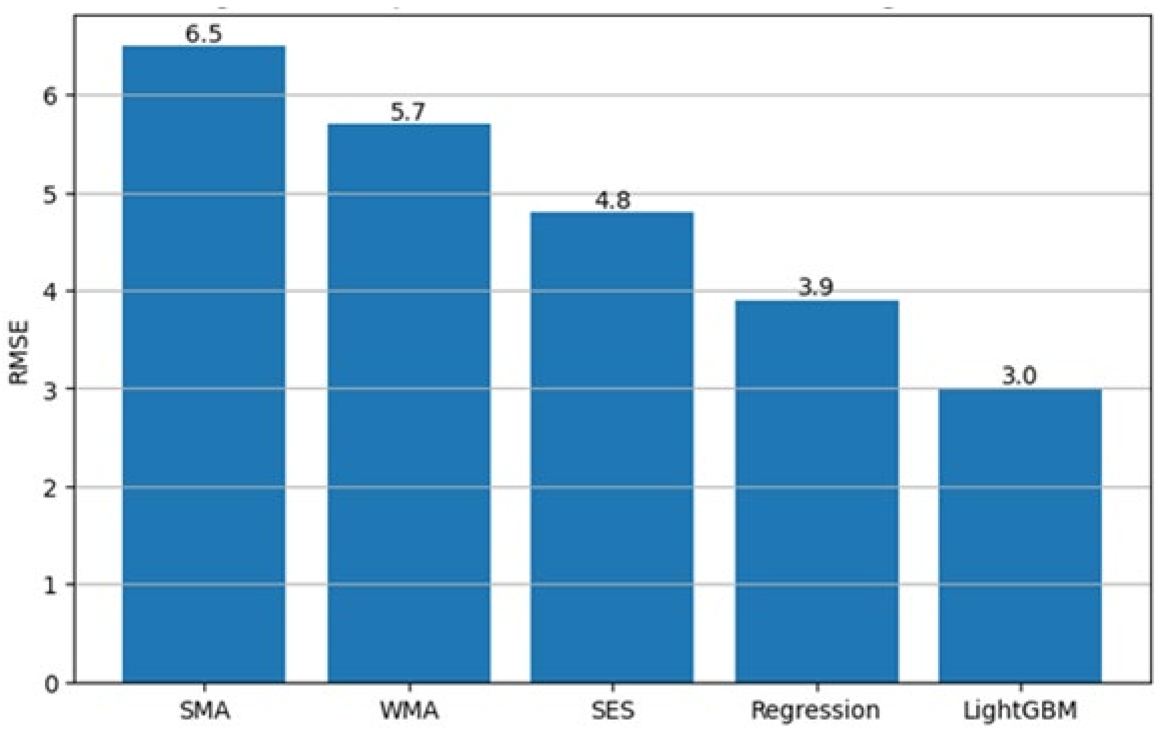

Fig. 4 Comparison of RMSE across forecasting methods

As shown in Fig. 4, the comparison of RMSE values confirms the trends observed in the MAE analysis. Classical forecasting methods exhibit relatively higher error levels, reflecting their limited ability to capture complex variations in demand. Among these methods, Simple Moving Average (SMA) shows the highest RMSE, indicating significant deviations from actual values, particularly in the presence of a growing demand trend. Weighted Moving Average (WMA) and Simple Exponential Smoothing (SES) provide improved results due to their ability to give more importance to recent observations. Linear regression demonstrates better performance by effectively modeling the overall trend in the data. However, the LightGBM model achieves the lowest RMSE, highlighting its superior capability to reduce large prediction errors and to adapt to dynamic demand patterns. These findings confirm that AI-based approaches offer enhanced accuracy and robustness, especially in environments characterized by variability. At the same time, the results reinforce the idea that classical methods remain relevant in stable contexts where simplicity and interpretability are key considerations.

3) Comparison of MAPE: In order to further assess the relative accuracy of the forecasting methods, the Mean Absolute Percentage Error (MAPE) is considered as an additional performance metric. Unlike MAE and RMSE, MAPE expresses the forecasting error as a percentage of actual demand values, providing a normalized measure that facilitates comparison across different scales. This metric is particularly useful in evaluating the practical significance of forecasting errors from a managerial perspective. Consistent with the previous analyses, MAPE is computed for all forecasting methods using the full dataset of 80 observations, ensuring comparability and robustness of the results. The comparison of MAPE values is illustrated in Fig. 5.

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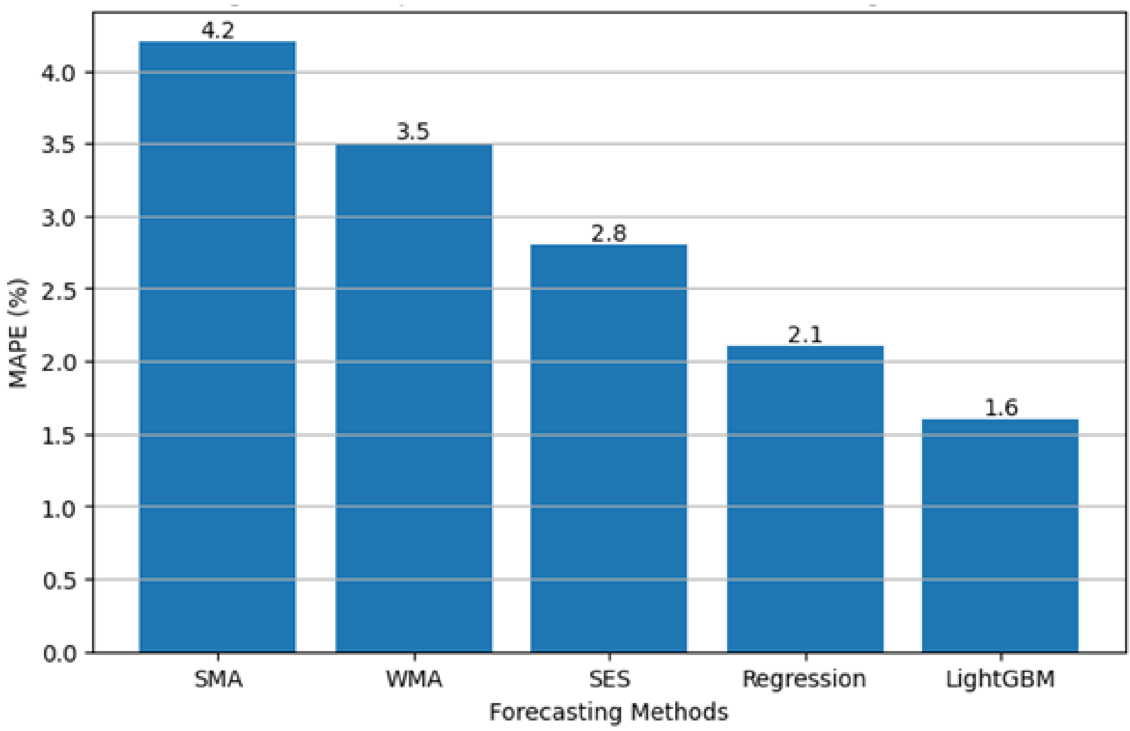

Fig. 5 Comparison of MAPE across forecasting methods

As illustrated in Fig. 5, the comparison of MAPE values highlights clear differences in forecasting performance across the considered methods. Classical approaches exhibit relatively higher percentage errors, indicating limitations in accurately capturing demand dynamics, particularly in the presence of an increasing trend. The Simple Moving Average (SMA) shows the highest MAPE, confirming its sensitivity to lag effects.

The Weighted Moving Average (WMA) and Simple Exponential Smoothing (SES) provide improved accuracy by incorporating recent observations, while linear regression further enhances performance by modeling the overall trend. However, the LightGBM model achieves the lowest MAPE, demonstrating its superior predictive capability.

From a managerial perspective, the lower MAPE values obtained by the AI-based model indicate a significant reduction in relative forecasting errors, which is essential for improving decision-making accuracy in inventory and operations planning. These findings are consistent with the results obtained using MAE and RMSE, reinforcing the robustness of the comparative analysis.

D. Comparative Analysis of Forecasting Methods

To provide a comprehensive and unified evaluation of forecasting performance, both classical methods and the AI-based approach are compared using three complementary metrics: Mean Squared Error (MSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). These indicators enable the assessment of forecasting accuracy in terms of error magnitude, sensitivity to large deviations, and relative performance. All models are evaluated using the same dataset of 80 observations to ensure consistency and fairness in the comparison. This unified framework allows for a direct assessment of the relative strengths and limitations of each method, including their ability to capture demand trends and variability. The results are summarized in Table 1.

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TABLE 1.

COMPARISON OF MODEL PERFORMANCE BASED ON MSE, MAE, AND MAPE

Method	MSE	MAE	MAPE
SMA (MMS)	22.05	4.45	2.24
WMA (MMP)	28.74	5.12	2.57
SES (LES)	57.08	7.31	3.65
Linear Regression	7.20	2.17	1.24
LightGBM (AI)	**5.10**	**1.85**	**1.05**

As shown in Table 1, the results highlight clear performance differences between classical forecasting methods and the AI-based approach. Among the traditional techniques, linear regression achieves the best performance, confirming its effectiveness in modeling the upward trend observed in the demand data. In contrast, SMA, WMA, and SES exhibit higher error values, reflecting their limited ability to adapt to dynamic demand patterns.

The LightGBM model outperforms all classical methods across the three evaluation metrics, achieving the lowest MSE, MAE, and MAPE values. This demonstrates its superior capability to capture complex and nonlinear relationships in the data, as well as its adaptability to demand variability. Overall, these findings confirm the added value of artificial intelligence in demand forecasting while also highlighting the continued relevance of classical methods in contexts where simplicity, interpretability, and ease of implementation are required.

V. Managerial Implications

The results of this study provide several important managerial insights. They highlight the need to adapt forecasting tools according to the operational context, demand variability, and the technological maturity level of the organization.

A. Choosing the Appropriate Method According to Context

The results show that forecasting performance varies significantly depending on the method used. Among the classical approaches, linear regression provides the best performance, demonstrating its ability to capture the upward trend observed in the demand data. In contrast, methods such as SMA, WMA, and SES exhibit higher error levels, reflecting their limitations in dynamic environments.

Classical forecasting methods remain relevant for stable and predictable environments, such as production systems with regular demand patterns or low variability. Their main advantages lie in their simplicity, transparency, and ease of implementation. However, in more dynamic and uncertain contexts, the AI-based model (LightGBM) clearly outperforms all classical methods. Its superior accuracy highlights its ability to model complex and nonlinear demand behaviors, making it particularly suitable for environments characterized by variability and uncertainty.

B. Towards a Gradual Hybridization of Approaches

The findings suggest that no single method is universally optimal across all contexts. While AI-based models provide higher predictive accuracy, classical methods offer better interpretability and easier adoption by operational teams. Therefore, organizations are encouraged to adopt hybrid approaches that combine the strengths of both paradigms: the stability and interpretability of classical models with the adaptability and predictive power of AI-based techniques. Such integration can support more balanced and effective decision-making processes.

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C. Skills Development and Organizational Transformation

The integration of AI-based forecasting models requires the development of advanced analytical and technical competencies within organizations. Managers should actively foster capacity building in data analysis, predictive modeling, and the use of decision-support tools, including programming environments (e.g., Python). Beyond technical aspects, this transition implies a shift from reactive management practices toward more proactive and data-driven decision-making processes.

D. Impacts on Operational Performance

Improved forecasting accuracy has direct implications for operational performance. The use of more accurate models, such as LightGBM, contributes to reducing forecasting errors, which in turn leads to better inventory control, reduced stockouts, and optimized production planning. Ultimately, enhanced forecasting reliability supports improved service levels and overall supply chain performance, reinforcing the strategic value of advanced forecasting techniques in modern operations management.

VI. Conclusion

This study aimed to compare the performance of classical forecasting methods and an artificial intelligence–based approach in the context of demand forecasting. Using a dataset of 80 observations, several models were evaluated, including Simple Moving Average (SMA), Weighted Moving Average (WMA), Simple Exponential Smoothing (SES), linear regression, and the LightGBM model. The comparison was conducted using multiple performance metrics, namely MSE, MAE, and MAPE, ensuring a comprehensive and robust evaluation framework.

The results demonstrate that forecasting accuracy varies significantly across methods. Among the classical approaches, linear regression achieved the best performance, highlighting its ability to effectively capture the upward trend present in the data. In contrast, SMA, WMA, and SES showed higher error levels, reflecting their limitations in handling dynamic demand patterns.

The LightGBM model outperformed all classical methods across the three evaluation metrics, confirming its superior capacity to model complex and nonlinear relationships. These findings emphasize the growing importance of artificial intelligence in demand forecasting, particularly in environments characterized by variability and uncertainty.

However, this study also highlights that classical methods remain relevant in stable and predictable contexts due to their simplicity, transparency, and ease of implementation. Therefore, rather than opposing these approaches, the results support a complementary perspective in which classical and AI-based methods can be combined to improve forecasting performance.

From a managerial standpoint, improved forecasting accuracy contributes to better inventory control, reduced operational costs, and more efficient production planning. Finally, this study opens several avenues for future research. Further work could explore hybrid forecasting models combining classical and AI techniques, as well as the application of these approaches to more complex and largescale datasets.

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