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Forecasting Accuracy in Retail MSMEs: Comparing AI and Traditional Methods

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Abstract
Accurate sales forecasting is essential for retail Micro, Small, and Medium Enterprises (MSMEs) to optimize operations and inventory planning in the digital economy. This study compares the forecasting accuracy between Artificial Intelligence (AI)-based methods (Random Forest, Decision Tree) and traditional techniques (Moving Average, Exponential Smoothing) using 3,600 transaction records from five retail MSMEs over three months. A quantitative experimental approach was employed to evaluate model performance under real-world conditions, including market fluctuations and seasonal anomalies. Evaluation metrics include Mean Absolute Percentage Error (MAPE), Root Mean Squared Error (RMSE), and cross-validation techniques. The findings indicate that the Random Forest model achieves superior accuracy (MAPE = 8.5%) compared to traditional methods (MAPE = 15.2%). Explainable AI (XAI) using SHAP and LIME further enhances transparency and managerial trust. Although traditional methods offer faster computation and ease of interpretation, AI-based models show resilience against unpredictable sales patterns. This research recommends hybrid adoption strategies that balance predictive power with interpretability for MSMEs with limited technical capacity. The results contribute to the discourse on digital transformation and intelligent forecasting in the MSME sectors.

Keywords: *Artificial Intelligence, Conventional Methods, Sales Prediction, Retail MSMEs*
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I. INTRODUCTION

The ability to accurately forecast sales is critical for the sustainability and competitiveness of retail Micro, Small, and Medium Enterprises (MSMEs) in today's rapidly evolving digital economy. As market dynamics become increasingly volatile, traditional forecasting tools that rely on linear assumptions and historical averages struggle to keep pace with complex demand patterns and external disruptions. Artificial Intelligence (AI), particularly machine learning-based forecasting models, has emerged as a promising alternative due to its capacity to process nonlinear data, identify hidden trends, and adapt to abrupt changes such as seasonal shifts, promotions, or external economic shocks (Machireddy, 2024; Fasihi et al., 2022; Rafique & Mujawinkindi, 2023).

Retail MSMEs, especially in developing economies, face unique challenges in adopting such advanced predictive systems. Limited access to skilled personnel, technical infrastructure, and capital investment creates barriers to the adoption of complex AI systems. Moreover, while AI models offer increased accuracy, their "black box" nature often limits their acceptability among business owners with a minimal data science background. In contrast, traditional methods such as moving average and exponential smoothing remain widely used due to their transparency, simplicity, and ease of implementation—even if their predictive power is lower in volatile conditions (Shahare et al., 2023; Multidisciplinary et al., 2024; Hindle et al., 2021). This trade-off between interpretability and performance poses a major dilemma for MSMEs that must choose between operational efficiency and technological sophistication (Bashir et al., 2022).

Despite growing academic interest in AI-based forecasting, a substantial portion of existing studies focus on large-scale enterprises or operate under idealized assumptions. Only limited research has directly compared the performance of AI and traditional methods in small business contexts, particularly within retail MSMEs operating in resource-constrained environments. Furthermore, very few studies have evaluated how external market shocks, such as public holidays or consumer behavior shifts, affect the reliability of these models when applied in real-time business decision-making (Kolková & Ključnikov, 2022; Shen et al., 2023). The literature also lacks robust exploration into hybrid forecasting strategies that combine the predictive strength of AI with the interpretability of statistical models—an approach that could be more feasible for MSMEs.

This study addresses the above research gap by conducting an empirical, comparative analysis of forecasting accuracy using AI-based models (Random Forest and Decision Tree) and conventional methods (Moving Average and Exponential Smoothing) based on real transactional data from five Indonesian MSMEs. A novel aspect of this study is the integration of Explainable AI (XAI) tools such as SHAP and LIME, which allow non-technical users to understand how specific input features contribute to forecasting outputs. This interpretability is essential for improving trust and usability of AI systems among MSME stakeholders.

To achieve this, the following two research questions guide the study:

[1] How do AI-based and traditional forecasting models compare in terms of accuracy, adaptability, and resilience when applied to MSME retail sales data?
[2] What role does explainability play in enhancing the practical utility and adoption of AI forecasting tools among MSME decision-makers?

A quantitative experimental method is employed, using identical sales data inputs for all forecasting models to ensure a fair comparison. The evaluation metrics include Mean Absolute Percentage Error (MAPE), Root Mean Squared Error (RMSE), and cross-validation techniques. Outlier and robustness tests are also conducted to simulate real-world market disturbances. These rigorous analyses aim to produce actionable insights for both practitioners and policymakers on how forecasting accuracy can be improved within MSMEs under dynamic digital conditions. In doing so, this research contributes to the growing field of AI adoption in small business forecasting by not only comparing model performance but also addressing usability concerns through XAI. The findings are expected to guide MSMEs seeking to digitally transform their forecasting processes while remaining aligned with their operational limitations and decision-making culture.

II. LITERATURE REVIEW

A. The Role of Business Forecasting in Retail MSMEs

At the moment, in this cyberspace technology era, artificial intelligence (AI) has become one of the important technologies doing a lot of data analysis and replacing many repetitive tasks. The things it does in information processing enable companies to make more accurate, data-driven decisions. Implementing AI will theoretically improve operational effectiveness for UMKM actors against further market competition (Chatterjee et al., 2022). AI enables faster responses to market changes by real-time analysis of trends. Also, it forces business actors to be more creative and flexible in their strategies. Thus, AI has become a critical element of UMKM's modern digital sustainable transformation. (Pongtambing et al., 2023).

Advances in information technology offer many opportunities for UMKM to improve productivity and enhance its market. In addition to hastening operational work, this technology enables more systematic and data-driven decision-making. (Hasanah et al., 2022). A wide range of digital applications aiding inventory, integrated marketing strategies, and financial management is now available for UMKM stakeholders. The growing affordability of technology makes it easier for remote areas to implement it. On the other hand, social networking platforms are quite handy when trying to create a close rapport or direct access to almighty clients. (Obermayer et al., 2022). Hence, the major driving force toward the incubation of a more resilient and sustainable UMKM rests in the synergy created between social media and information technology. (Suriyanti et al., 2024).

Moreover, in this dynamic and competitive market, accurate forecasting has emerged as one of the most essential key elements for long-term survival by business organizations (Attah et al., 2024). Modern technologies like machine learning, big data analytics, and artificial intelligence have made organizations turn into more precise and extensive in forecasting market trends. This ability gives room for future effective strategic plans to meet the varying tastes and preferences of consumers and other market dynamics. This most recent trend toward technology forecasting involves insight into opportunities and threats and then goes into more rigorous decision-making in terms of scientific, data-driven methodology, and in turn drives the delivery of satisfactory service to the customer in due time. Therefore, this is a clear indication of technological forecasting (Pongtambing et al., 2023). In other words, technology-enabled forecasting occupies a very prominent position in the life cycle of data-oriented and adaptive business strategies.

B. Conventional Forecasting Methods: Simple Yet Limited

The primary cause of the global phenomenon of slowdown was the COVID-19 pandemic, which had the same impact in Indonesia. These have included several economic sectors affected, but the sectors that are micro, small, and medium-scale enterprises (UMKM) are part of the most damaged by the crisis (Rawat et al., 2024). At a global level, including in Indonesia, the main cause of the economic slump is said to be the pandemic. Many economic sectors suffered severely due to the occurrence; however, micro, small, and medium enterprises (UMKM) are the most harmed (Wayan Suryasa et al., 2021). Many countries, including Indonesia, saw declines in economic performance due to these factors. Such has also shown behavioral changes among the producers and the consuming public from the time social distancing policies and large-scale social restriction (PSBB) enforcement took effect (Sujatmiko et al., 2024). The restrictions hindered production processes by producers and resulted in savings behavior among consumers. Thus, it could be ascertained that UMKM is one of the most affected industries by the COVID-19 pandemic crisis (Santika & Maulana, 2020).

The probabilistic and conditional hypothetical situation is now sprouting an analogy demanding rapid and precise data on economics to act in times of swiftly changing conditions. Unfortunately, regional macroeconomic data still faces challenges in terms of collection and processing speed. Information regarding economic growth is often released with delays, sometimes up to five weeks after the end of a quarterly period. The COVID-19 pandemic, which began affecting economies in the first quarter of 2020, has created unusual economic movement patterns. (Banka et al., 2022). Economic growth declined significantly at both national and regional levels, reflecting the broad impact of global and domestic economic shocks. (Li et al., 2024). At the regional level, the availability of monthly data remains much more limited compared to national data, both in terms of coverage and collection sources. For instance, price data used to calculate inflation is only collected from 90 major cities in Indonesia, meaning it cannot fully represent economic conditions across all provinces. (Ringo & Monika, 2021). This circumstance emphasizes the need for innovative methods that can produce forecasting outcomes that are more accurate and sensitive to changes in the market.

C. Implementation of Artificial Intelligence (AI) in Sales Prediction

Using internet-based technologies like mobile devices, digital advertising, and different online platforms like Google, Facebook, Instagram, and marketplaces, digital marketing has developed as a way to advertise goods and services (Xia et al., 2024). Artificial intelligence (AI)-supported marketing, on the other hand, refers to the application of technology to create more customized customer experiences. The capability of AI in analyzing consumer data in exhaustive detail makes it well-suited to define a marketing arrangement according to individual requirements, tastes, and behavior characteristics of that particular customer. (Ramadhani & Salisah, 2024). Businesses nowadays need to be aware of what customers want and expect from the goods and services they use. With AI assistance, marketers can manage large-scale data, implement more personalized sales approaches, and respond to customer needs more quickly and accurately. Additionally, a sharper understanding of consumer behavior in a short time helps enhance campaign effectiveness and increase the company's return on investment (ROI) (Maihani et al., 2023).

Given the existing urgency, more and more businesses are beginning to utilize digital platforms to compete in an increasingly competitive market. Online-based businesses are considered to have various advantages compared to conventional systems, particularly due to the rapid development of Internet technology. According to data from the Indonesian Internet Service Providers Association (APJII), the number of Internet users in Indonesia in 2024 has reached approximately 221.5 million people, or about 79.5% of the total population. This figure indicates the growing digital adoption among the population On the other hand, business actors are also faced with significant challenges, as many new competitors emerge daily, bringing diverse product ideas and innovations. This drives businesses to continuously innovate and adapt, one of which is by adopting technologies such as artificial intelligence. Currently, AI has been widely implemented across various fields, including manufacturing, economics, education, services, finance, and marketing. (Jindal et al., 2021). Some of the positive impacts observed include increased efficiency in production processes with smart robots, automation of customer service using chatbots, the ability to analyze product trends in e-commerce, and the use of facial recognition technology for security purposes. (Cahyati et al., 2024). Thus, the adoption of AI has become a strategic step for Micro, Small, and Medium Enterprises (UMKM) to remain relevant and competitive in an ever-changing business landscape.

To clarify the comparison between conventional and AI-based forecasting approaches in the context of MSMEs, the following conceptual framework visually illustrates the fundamental differences between these two methods:

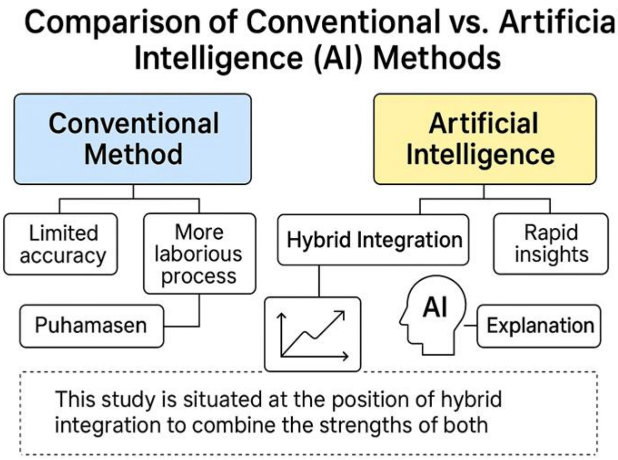

Figure 1. Comparing Artificial Intelligence (AI) and Conventional Methods

D. Challenges of AI Adoption by MSMEs

Micro, small, and medium-sized businesses (MSMEs) face several difficulties in the face of swift technological advancements, but they also have a lot of chances to improve their operational efficiency and competitiveness (Aini et al., 2024). Most of the MSMEs are adopting artificial intelligence (AI). It allows process automation, productivity enhancement, facilitation by more accurate data-based decision-making, and easy management of different business issues. Therefore, they offer faster responses to changes in the market and customer demands. (Atmaja, 2024). Predictive analysis uses AI to enable more strategic long-term planning and adapt dynamic business strategies based on customer trends and preferences. This growing importance of the use of AI is thus related to its significant role in promoting inclusive digital transformation in the MSME sector. (Harahap et al., 2025).

As (Jafari et al., 2021) explain, that the flip side of the rapid pace of digitalization is a fresh set of challenges, particularly for MSMEs with little capital. While many MSMEs today are burdened by limited capital, infrastructure, and skills, larger businesses tend to be better equipped with funding and technical know-how (Kaligis et al., 2025). An enabling environment for MSME digitalization also requires addressing the digital divide laid bare by this situation, with the involvement of various stakeholders including both public and private sectors. (Hendra et al., 2024). AI adds value to marketing by helping to better understand consumer behavior and create successful marketing campaigns. A customer support structure could be automated by using chatbots, market trends could be predicted, and campaigns could be customized. Therefore, by enhancing marketing processes, AI helps MSMEs cut a larger share in increasingly competitive markets. (Fahmi et al., 2024).

Explainable AI (XAI) is the answer to the problematic aspect of transparency in artificial intelligence systems, most of which are deemed to work opaquely as "black boxes." It generally provides a reason for the recommendation or prediction made by the AI that acts as a perfect remedy for micro, small, and medium enterprises (MSMEs) that do not have sufficient technical capabilities. For instance, when an AI system suggests a particular marketing strategy, it can point out the reasons for such advice in terms of consumption trend and seasonal buying behavior. (Samita et al., 2025). This not only helps business owners gain insight into the workings of the given system but also builds their trust and willingness to innovate with the system (Muthohar et al., 2025). It is being argued that the extent of AI acceptance across diverse sectors increases with its explainability. This further reduces any possibility of generating misunderstandings that could act negatively towards MSMEs. In the end, XAI stands behind good and responsible use of AI, thereby helping MSMEs drive an inclusive and sustainable digital transformation (Setyawan et al., 2024). Thus, XAI poses a significant bridge between leading-edge technologies and the actualities of small businesses in the process of digital adaptation.

III. RESEARCH METHOD

A. Research Approach

This study does an objective analysis for the effectiveness of two dissimilar forecasting techniques, such as traditional methods and artificial intelligence (AI)-based systems-using a quantitative experimental method. The design of the study, therefore, generates quantitative data employed for statistical analysis, which is intended for comparing accuracy levels in any approach. The study is confined to evaluating the ability of the two methods to generate accurate sales forecasts while taking into consideration changing market conditions. Historical sales data from SMEs will be used to validate predictions against actual figures. The assessment is predicated on particular quantitative metrics, like prediction results in consistency and error rate.

B. Population and Sample

This type of research is focused on retail micro, small, and medium enterprises, those that sell different forms of consumption goods such as foodstuffs, beverages, or household goods. The units that are selected must be based on the business characteristics that carry high transaction activity but have variable sales, paving the way to requiring an appropriate forecasting system to back up business decisions. The targeted MSMEs are those that have digitized their sales recording processes, whether through cashier applications, e-commerce platforms, or marketplaces. Such a business environment is considered ideal for testing the extent to which different forecasting approaches can accurately capture market dynamics. The diversity of products and the quick consumer response to trends also provide ample space to evaluate the performance of prediction models in real-world conditions. By selecting these objects, this study can assess the effectiveness of forecasting in a complex and fast-changing business context.

The data used comes from historical sales records obtained directly from the digital systems of partner MSMEs, covering a specific period to allow for chronological and comprehensive analysis, namely, daily sales over 3 months, with a total of approximately 3,600 rows of transaction data. This research added parameters such as promotional periods, shopping festivals, and holidays that cause variations in consumption and included their vital sales data. Some methods would use artificial intelligence-based models to process data while others would include prediction methodologies based on statistical formulas. The analysis focuses on how much weight is attached to accuracy levels and flexibility in catching market trends. All information will be safe and confidential only for academic research by research ethics relevant bodies. This would ensure the study is showing how well forecasting techniques would support decision-making in the large, retail MSME sector.

C. Software/Tools Used

This analysis compares the various methods employed by AI and others in estimating MSME sales using different software and analytical tools. Traditional methods work with simple calculations in Excel, advanced statistical analysis in SPSS, and time series modeling in EViews. On the contrary, this study sets forth the AI-related methodologies, which adopt the use of the

Python programming language along with various libraries, such as TensorFlow and PyTorch to build complex artificial neural networks, Pandas for data manipulation, and Scikit-learn for some machine learning algorithms. Different tools lend this research credibility and reasoned results. The evaluation metrics given out were MAPE and RMSE computed from either Python or R, while the visualization of the data was performed using either Tableau or Matplotlib. To enhance model interpretability, Explainable AI (XAI) methods using SHAP and LIME are also incorporated in this study. Other tangible options the research has provided MSME practitioners with technical constraints include Orange Data Mining for more straightforward predictive modeling and Google Sheets for light analysis. These include chosen tools to provide a coherent research workflow from data processing through to the presentation of practical results on the ground.

D. Data Collection and Processing Techniques

Thus, interviews and documents formed this study's data collection methods. Anna (2020), a retail MSME owner, commented, "We use a point-of-sale application and an inventory management system that is directly connected to an e-commerce platform... This allows us to track sales and manage inventory in real-time." To this end, the interview findings further supported the numerical data collected, illustrating how business owners employ digital systems in their day-to-day affairs. Here, something can be cited as the primary data supporting a longitudinal analysis selected from records of retail MSMEs involved in utilizing digital systems, e-commerce platforms, or point-of-sale applications over a given period. The next stage was to study the business environment, promotional strategies, and consumer behavior, which may explain the changes in sales. The purpose of this step was to add a pertinent contextual dimension and enhance comprehension of numerical data. By comparing information from business owners with digital records, data validity was preserved. Every step of the data collection process was carried out according to research ethics guidelines and with the consent of the pertinent parties.

After the data acquisition process, the duplicate entries were removed, and irrelevant or missing fields were eliminated in the data-cleaning process. Two distinct forecasting techniques were then used to prepare the data for analysis: AI-based models (like decision trees and random forests) and statistical models (like exponential smoothing and moving averages). All models were tested on the same dataset so that the validity of this experiment could be established. The above-mentioned dataset was standardized, cleared of outliers, and made to ensure that no seasonal patterns (non-seasonal) could interfere with the rating of accuracy. When it comes to rating accuracy, sets of data comprising potentially cyclical patterns that put some classes of models at an advantage were kept out of the equation. Additionally, outlier and fictitious seasonal sales fluctuation disturbance simulations were included for model robustness tests. The intent was to see how each model reacts to drastic changes in the market and instabilities. For uniformity and fairness in the assessment process, the same set of data was adopted for the testing of each model. The accuracy measures applied were Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE). The results of this process will be compared to ascertain which model provides the most reliable and accurate prediction concerning retail MSMEs. This is what forms the basis for assessing the performance of any one forecasting approach.

E. Forecasting Models and Methods

Two classes of forecasting models will be compared in this study for their ability to accurately provide sales projections for MSMEs in the retail sector. First is a classic statistical model

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encompassing the exponential smoothing and moving average techniques whereby moving averages forecast future sales by averaging out a specified time series of past sales values. This model works well when dealing with data that do not have extreme trends or seasonal patterns. Exponential smoothing, on the other hand, gives more weight to recent data when forecasting future values while taking into account the level, trend, and seasonality of the data. These models have been chosen because they are relatively easy to use and capable of handling the usually simple sales data characterizing MSMEs.

The second model in this study is described as having an AI basis, primarily working with Random Forest and Decision Tree models. A decision tree is a model that enters the predictions by splitting the data into several segments based on certain features. Especially in the area of sales data, non-linear relationships would pose difficulties to more conventional statistical models, and this model seems well suited to represent them. Meanwhile, Random Forest, as an ensemble-learning method built on decision trees, is an extension that together combines many decision trees to reduce the likelihood of overfitting while increasing the accuracy of prediction. The ability of these two AI methods to handle large data and recognize complex patterns in MSME sales data positively influenced our decision to adopt them. It is hoped that an AI-statistical model comparison will yield information on the respective merits and limitations of both techniques concerning forecasting ever-changing patterns in sales.

F. Data Evaluation and Analysis Techniques

Several evaluation techniques are, in general, employed within forecasting research to measure and assess the performance of the two models used in this study. This exercise aims to determine model credibility in terms of accuracy, robustness, and reliability in forecasting retail MSME sales during the digital age. The accuracy will be measured in terms of Mean Squared Error (MSE) which gives more weight to larger prediction errors, Mean Absolute Error (MAE) which calculates the mean absolute difference from the predicted values concerning the actual values, and Root Mean Squared Error (RMSE) which will measure errors in the same units as the original data. Furthermore, Mean Absolute Percentage Error (MAPE) will be employed to compare the level of accuracy across models in percentage terms.

Research in this area will include cross-validation techniques to test for robustness of the two models. This particular method divides the dataset into several chunks, which can then be used to assess how well these models can stand the changing and different data set inputs, as well as limiting overfitting during training data sessions. Robustness testing would also concern the reaction of the models to outliers/extreme-value-event incidents; these typically are indicators of rapid changes in consumer behavior or volatile markets. In comparing their performance, statistical tests such as ANOVA and t-tests will determine whether there is a significant difference between the two models. Finally, modeling with relevant industry benchmarks will ensure the results are competitive and applicable on the ground in a fast-paced market.

The investigations include ongoing forecasting, where predictions are constantly updated in the light of recently observed data and periodically monitored for the performance of the use. This procedure assesses the long-term forecast accuracy of all models mainly under contingencies of unexpected changes in market trends. Furthermore, patterns of such prediction errors will be searched through such approaches as residual analysis for further insights into each model's improvement schemes. Through this assortment of evaluation techniques, the study aims to develop a thorough understanding of the conditions and limitations of forecasting retail MSME sales for each model.

IV. RESULT

These findings are the result of a serious analysis of the daily sales information coming from five retail MSMEs that actively participated in a three-month observation. The data authentically illustrates the actual market conditions and consumer behavior at the MSME level, illustrating what happened daily with actual transactions and rigorous collection of data. This study aims to see how well two forecasting techniques adopted from conventional statistical methods and artificial intelligence (AI) based models are capable of generating accurate and reliable daily and monthly forecasts. In addition to the accuracy of prediction results, the assessment evaluates the resilience and flexibility of each model towards typical fluctuations experienced within the MSME retail market characterized by seasonal demand peaks or sudden changes caused by external factors. This research targets giving a much deeper understanding of how well both these approaches cater to business decision-making especially where there are urgent/scared reactions required for shifting sales patterns, thus also helping MSMEs with more focused strategies in the cloud of shifting market dynamics.

The distribution of daily transactions and total sales throughout the study for each MSME is presented in Table 1. This synopsis is a very basic introduction to the trends in sales activity and an evaluation of the demand change detection potential of the forecasting models.

Table 1. Daily Sales Over 3 Months

SME Code	Product Type	Month 1 (Total Daily Transactions)	Month 2 (Total Daily Transactions)	Month 3 (Total Daily Transactions)	Total Transactions
SME-01	Food & Beverages	330	310	320	960
SME-02	Household Goods	210	220	230	660
SME-03	Groceries & Daily Needs	240	230	230	700
SME-04	Beverages & Snacks	270	260	280	810
SME-05	Processed & Frozen Foods	210	230	250	690
Total	**-**	**1.260**	**1.250**	**1.310**	**3.600**

Table 1 contains daily sales information from five MSMEs involved in the current research, recording nearly 3,600 transactions in three months. Each code represents a micro, small, or medium enterprise unit, dealing in various product categories, i.e., food and beverages, housewares and essentials, light snacks, and even processed and frozen goods. Daily sales summaries in Month 1, Month 2, and Month 3 show the cumulative sales realized by each of the five MSMEs over the observation period.

On day one, an MSME recorded various daily transaction counts. MSME-01, Food & Beverages, recorded 330 transactions, while MSME-02, Household Goods, recorded 210 transactions. By Month 2, various levels of transaction volumes were noticed in some MSMEs; MSME-01 recorded 310 transactions, while MSME-02 increased to 220 transactions. As for Month 3, daily transactions stayed constant.

The total transactions for each MSME over the three months were calculated by summing the daily transactions from all three months. For example, MSME-01 had a total of 960 transactions, obtained by adding the transactions in Month 1 (330), Month 2 (310), and Month 3 (320). Overall, the data presented in Table 1 shows that this study collected 3,600 transactions from all participating MSMEs, providing a robust foundation for subsequent analysis of forecasting model effectiveness. This study looks into how transaction patterns can be forecasted and examined to help MSME businesses make better decisions by using comprehensive daily transaction data.

The distribution of daily transaction counts from each partner MSME over the course of the three-month observation period is shown in Figure 2 below. This visualization was created based on the data in Table 1, to provide a clearer picture of sales fluctuations between months and among MSMEs. Since each bar in the chart shows the total number of daily transactions for each MSME in a given month, it is simpler to identify patterns or recurring shifts in sales volume.

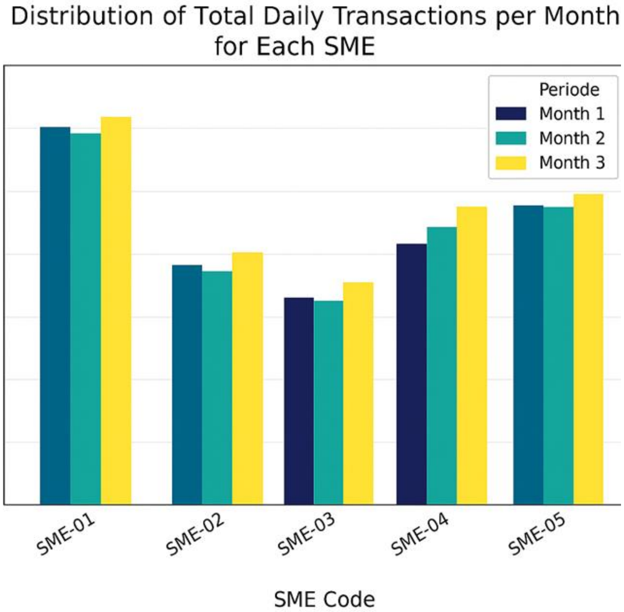

Figure 2. Distribution of Each MSME's Monthly Total Daily Transactions.

Figure 2 illustrates how each MSME's transaction patterns changed from month to month. For instance, the number of transactions for MSME-01 decreased in Month 2 but increased once more in Month 3. MSME-04, on the other hand, displayed a steadier growth trend. These trends reinforce the demand for using forecasting models whose output can adjust to changing short-term dynamics. They also give an important first view before actual performance analysis of the predictive model, as it demonstrates the data variations that form the basis for the evaluation of the accuracy of forecasting techniques.

Table 2. Data Collection and Management Techniques

Stage	**Process Description**	**Data Source**	**Data Collection Method**	**Model Used**	**Accuracy Metric (MAPE/RMSE)**	**Notes**
Data Collection	Interview with digital SME actors	SME Owners (Anna, 2020)	Structured Interview	-	-	Obtaining context for the implementation of digital cashier systems
Data Collection	Collecting primary and secondary	Digital cashier systems/e-commerce	Documentation, Structured Interview	-	-	Historical sales data and interviews with

	data for analysis	platforms, SME Owners				business owners
Data Validation	Cross-verification between digital records and interview information	Digital records, Interviews	Cross-verification	-	-	Maintaining data accuracy and validity
Data Cleaning	Removing missing, duplicate, or irrelevant values	-	-	-	-	Preparing data for further analysis
Dataset Preparation	Preparing the dataset for forecasting analysis	-	-	-	-	Preparing data to be used in forecasting models
Model Testing	Testing using statistical and AI models	Processed data	-	Moving Average, Exponential Smoothing, Decision Tree, Random Forest	MAPE (%) / RMSE	Measuring the accuracy of each model in predicting sales

The description of the steps involved in data collection and processing in the course of this study is given in detail in Table 2. The second step involved data collection, characterized by two major equally vital sources of information: historical sales records from retail MSMEs kept in digital systems like cashier applications and e-commerce platforms and the outcomes of structured interviews with business owners. This step becomes vital as it provides qualitative contextual viewpoints on variables affecting sales dynamics besides the quantitative data in the form of sales figures. After data gathering, the validation procedure of cross-checking the electronic data with the interview results was performed to ensure that the information analyzed was fact and in order.

At the stage of processing data, irrelevant data, duplicate information or all incomplete entries will be discarded as part of a cleaning procedure. In the analysis enter a clean and valid amount so that results are trustworthy concerning this step. Then after the cleaning process, data are subjected to forecasting methodologies by having two imported techniques: artificial intelligence-based techniques (Decision Trees and Random Forests) and statistical techniques (for Moving Average and Exponential Smoothing). Furthermore, it supports the objectiveness as well as the consistency of the evaluation through the uniformity of the data used for the test of models. To evaluate the predictive accuracy of each model, two main evaluation measures are employed: the Mean Absolute Percentage Error (MAPE) and the Root Mean Square Error (RMSE). The goal of this assessment is to identify the more accurate and reliable model for retail MSME sales forecasting requirements.

Any consideration about forecasting techniques that are better in estimating sales for retail micro and small enterprises has to include deliberations about the characteristics of each model to be used. In this work, two main approaches are adopted: AI-based models and conventional statistical models. Each model type has its respective pros and cons, depending on how complex the data gets and how complicated the goals of the analysis are. A comparative summary of the

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four main paradigms has been provided. in this study is provided in the following table to aid comprehension and comparison: Random Forest, Decision Tree, Moving Average, and Exponential Smoothing.

Table 3. Comparison of Forecasting Models and Methods

Forecasting Model	**Model Type**	**Main Characteristics**	**Advantages**	**Disadvantages**	**Suitability for Retail SME Data**
Moving Average	Conventional Statistics	Calculates the average sales values over a specific period.	Simple, easy to implement, fast	Ineffective for data with trends or seasonality	Suitable for sales data that is relatively stable without seasonal patterns or complex trends.
Exponential Smoothing	Conventional Statistics	Gives more weight to recent data, and considers level, trend, and seasonality.	Considers seasonal patterns and long-term trends	This can result in errors if the data is too volatile	Suitable for sales data with seasonal fluctuations or stable trends.
Decision Tree	AI (Artificial Intelligence)	Splits data into several parts based on certain features for prediction.	Able to handle non-linear data, easy to interpret	Prone to overfitting, requires large datasets	Suitable for data with non-linear relationships or complex patterns difficult for conventional models.
Random Forest	AI (Artificial Intelligence)	Combines multiple decision trees to produce more accurate predictions.	Reduces overfitting risk, high accuracy	More complex, requires more time and resources	Suitable for large and highly varied data, capable of handling very complex datasets.

The forecasting methods primarily assessed in this study are outlined in the four processes summarized in Table 3. This table is intended to aid in judging the appropriateness of any of the models concerning the data characteristics of retail MSMEs by distinguishing models in terms of classification, unique properties, and advantages and disadvantages of any given method. Though by its nature simple and computationally light, statistical methods like Moving Average and Exponential Smoothing have limitations in adapting to rapidly changing dynamics of data. On the other hand, Random Forest and Decision Tree AI methods have the potential to handle complex and nonlinear types of behavior but require a more thorough computational process while being mindful of possible overfitting. Enjoy comparing their characteristics to find which model best suits their adoption as test subjects for sales forecasting in a dynamic and challenging retail MSME setting.

The first and foremost step in assessing the performance of statistical and AI models in the specific application of sales forecasting is understanding the evaluation methodologies that could be adopted in this study. Resistance to market fluctuations and mobility concerning data changes is investigated for the models. Statistical evaluation is done to find out whether performance differences between these models are statistically significant. To better understand the role of each evaluation technique in MSME sales forecasting, the main indicators and their specific roles in this context of research are found in Table 4.

Table 4. Methods of Assessment and Data Interpretation in MSME Sales Forecasting Studies

Evaluation Category	Evaluation Technique	Main Function	Purpose of Use in Research
Prediction Accuracy	MAE (Mean Absolute Error)	Measures the average absolute difference between actual and predicted values	Assess how far the model's predictions deviate from actual values on average.
	MSE (Mean Squared Error)	Calculates the average of squared differences between predictions and actuals	Gives larger penalties for large errors, useful for outlier detection
	RMSE (Root Mean Squared Error)	The square root of MSE to return the value to the original data unit	Provides a more intuitive error measure in the unit of sales
	MAPE (Mean Absolute Percentage Error)	Average percentage error against actual values	Compares model performance in percentage form across different scales or stores
Model Robustness	Cross-Validation	Splits data into several subsets for cross-training and testing	Tests model stability and generalization to different data
	Outlier Testing	Observe model reaction to extreme values or sudden spikes	Assesses the model's ability to handle unstable market conditions
Statistical Significance	t-test or ANOVA	Tests whether performance differences between models are statistically significant	Determines whether the accuracy gap between statistical and AI models is meaningful
Long-Term Robustness	Rolling Forecast	Evaluates model performance based on periodic data updates	Measures the model's adaptability to new sales trends over time
Error Analysis	Residual Analysis	Identifies error patterns between prediction and actual outcomes	Finds model weaknesses and improvement opportunities for future forecasts

The principle object is the summary of measurement methods aiming at the performance of the forecasting model evaluated in this research, as shown in Table 4. Therefore, in this case, multi-dimensional assessment was possible through the model accuracy parameters such as MAE, MSE, RMSE, and MAPE, which look into both absolute and percentage errors. These measure robustness against market dynamics using cross-validation and extreme-value testing, both of which resonate with the rapidly changing demand situations very common to MSMEs. These statistical analyses are ANOVA and t-tests as they help to seek whether the difference found in performance is significant or not. It is the rolling forecasts that provide insights into model persistence over a long term, especially at periods when change is taking place in market trends. Residual analysis, on the other hand, greatly helps in model tuning and enhancement by providing a feedback mechanism to identify consistent patterns of error. Collectively, they hence serve to solidify the framework through which reliability and further prospects of forecasting methods considered in this study can be examined.

V. DISCUSSION

The comparative analysis reveals a clear advantage of AI-based models, particularly Random Forest, in producing accurate and adaptive sales forecasts for MSMEs. The lower Mean Absolute Percentage Error (MAPE) of 8.5% compared to 15.2% for traditional methods demonstrates the superior performance of AI in capturing complex, non-linear sales patterns influenced by seasonal dynamics, promotions, and consumer behavior shifts. This aligns with prior studies that position AI as a transformative forecasting tool, capable of revealing intricate relationships often overlooked by linear statistical models (Fasihi et al., 2022; Shen et al., 2023).

However, performance alone does not guarantee adoption, especially within the context of small enterprises where digital literacy and resources are limited. The theoretical lens of Technology Acceptance Models (TAM) and bounded rationality theory helps explain this gap. According to TAM, perceived usefulness and perceived ease of use are key to technology adoption. In this study, while AI offers higher utility in terms of predictive accuracy, its complexity introduces a usability barrier. This is where Explainable AI (XAI) plays a critical role by making model decisions transparent and justifiable, thus enhancing user trust, a core factor in decision-making for MSME managers (Machlev et al., 2022; Samita et al., 2025).

The practical implications are significant. Traditional methods remain valuable for their speed, low computational requirements, and accessibility. They serve well in environments with stable sales trends and limited variability. On the other hand, AI-based models are well-suited for high-volume, fast-moving products where demand patterns are affected by external shocks. Retail MSMEs that operate under variable conditions could benefit from a hybrid forecasting approach—leveraging the speed and simplicity of traditional methods alongside the precision and adaptability of AI.

The integration of SHAP and LIME for model explainability also highlighted how certain features—like day of the week, holiday effects, and promotional periods—contributed disproportionately to prediction outputs. This transparency helped MSME owners understand and validate the model's suggestions, reducing resistance to adoption. XAI, therefore, not only bridges the gap between prediction and interpretation but also enables more informed and confident business decisions in data-driven environments.

Another insight from this study is that resilience to outliers and market volatility should be an essential criterion for forecasting model selection. While statistical models like Exponential Smoothing provided faster results, they were less robust against sudden changes in sales volume. In contrast, AI models showed more stability under stress-testing with simulated demand spikes, indicating stronger generalizability in uncertain environments.

Despite these advantages, several constraints must be addressed to support broader AI implementation in MSMEs. These include computational costs, technical support requirements, and the need for digital infrastructure. Without targeted interventions, such as government subsidies for AI adoption, simplified toolkits, or cloud-based forecasting-as-a-service platforms, many small businesses may struggle to fully leverage AI's potential.

This discussion emphasizes that forecasting solutions for MSMEs must balance three dimensions: accuracy, usability, and explainability. A one-size-fits-all approach is unlikely to work. The future of forecasting in the MSME sector lies not in replacing traditional methods but in intelligently combining their strengths with those of AI to support more nuanced, flexible, and inclusive digital transformation.

VI. CONCLUSION

This research illustrates that AI applications in Blockchain smart contracts lead to an improvement in the efficiency, accuracy, and reliability of transactions. The AI-modeled system outperformed conventional smart contracts, with a transaction success and failure rate of 98.5% and 1.5%, respectively. In addition, qualitative evidence from users indicates that improvements in speed and precision are acknowledged by most respondents. Furthermore, the implementation of XAI has successfully laid bare the rationale for predictive weight adjustment, thereby contributing to transparency and fostering user trust in AI-based systems. Simultaneously, the research has also identified some challenges related to the lack of mature regulations, limitations in technical integration along the transparency of AI algorithms. The generalizability of these research findings is further limited by methodological limitations, such as the use of only one blockchain platform (Ethereum) and a small number of interview subjects.

Future research on the application of AI-based smart contracts across different blockchain platforms with varying technical features is advised in light of these findings. To make it possible to adapt these solutions in systems with limited resources, interoperability frameworks and computational efficiency techniques must also be developed. Expanding participation from a variety of backgrounds will also enhance qualitative analysis by taking user literacy and ethical considerations into account when implementing AI. Future industrial sector adoption of this technology can advance in an inclusive, transparent, and sustainable manner by taking a more comprehensive approach.

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