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THE ROLE OF ARTIFICIAL INTELLIGENCE IN ENHANCING BUDGET FORECASTING FOR SMES AMID ECONOMIC UNCERTAINTY

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Abstract

The present economic situation poses significant barriers for Small and Medium Enterprises (SMEs) to forecast their finances and develop budget predictions. Traditional budget planning systems break down as markets become unpredictable, leading organizations to forecast wrong data and assign improper resources. The current study determines Artificial Intelligence (AI) technology as an optimized solution for improving SME budget prediction performance while exploring its design methodology using predictive analytics and machine learning procedures. This research examines AI models containing neural networks with decision trees and regression analysis to prove their ability to increase financial forecasting precision among SMEs. Studies utilized a mixed methodology that analyzed quantitative AI tool performance measurements from SMEs and performed qualitative examinations of SMEs that adopted AI-based technologies. AI forecasting systems surpass traditional forecasting approaches through evaluation because they deliver superior results, allowing Small and Medium Enterprises to make crucial decisions using dependable information under uncertain economic circumstances. This research studies the multiple barriers that stop SMEs from adopting AI, such as lack of resources, insufficient expertise, and difficulties securing their data. Through its research, the study gives actionable guidelines about AI budget implementation to assist SME owners, financial planners, and policymakers in sustaining business growth while advancing sustainability. The study contributes to financial management AI knowledge and provides SMEs with a successful strategy to utilize AI tools for budget predictions during uncertain economic times.

Keywords: Artificial Intelligence, Budget Forecasting, SMEs, Economic Uncertainty, Predictive Analytics.

1. Introduction

1.1 Background of the Study

Numerous countries depend on small and medium enterprises (SMEs) as their economic backbone since these companies comprise 90% of total businesses and create more than half of all worldwide employment, as measured by World Bank statistics. Due to their ability to adapt, innovative capabilities, and proximity to their customers, SMEs play a fundamental role in economic and community development. The identical features which allow SMEs to be flexible and innovative simultaneously create vulnerabilities to economic disruptions. Financial planning operations of SMEs experience significant stress as inflation volatility happens alongside interest rate fluctuations and changes in supply chains and consumer preferences in uncertain economic conditions.

Strategic financial planning depends on budget forecasting as its core element to assist SMEs in managing their resources effectively and forecasting future cash flows for evaluating potential investments. Small and medium enterprises mainly use conventional and introductory forecasting systems that fail to detect present market evolution properly. The data linkage capabilities and environmental adaptability remain poor in these forecasting methods because they generate essential prediction errors. Businesses operating under strict economic conditions need adaptable forecasting approaches instead of conventional methods because the latter provide limited strategic value.

Artificial Intelligence (AI) functions through predictive analytics, and machine learning (ML) has become an effective financial decision-making tool. AI systems use their data discovery skills to search implicit patterns from large datasets, which helps them generate fast, accurate predictions. AI forecasting technology is effective in banking operations, Retail, and logistics functions since it enhances accuracy while decreasing strategic decision-making bias using data. SMEs have not been able to fully leverage AI technology because they encounter multiple barriers, including challenging technology integration, extensive implementation, and limited digital resources.

The successful application of AI in SMEs depends on companies identifying specific methods that work with their business organization and specific operational requirements. Regarding data collection, IT, personnel, and decision-making, SMEs operate with capacities lower than large businesses and focus on operational needs before considering future innovation. Businesses can obtain advanced analytics capabilities at a low cost through user-friendly AI solutions that support small firms available on the market. During economic turmoil, SMEs can use AI as a crucial framework for maintaining operations while building competitive advantages for their financial processes.

1.2 Problem Statement

SMEs' operational stability and long-term viability face direct danger from economic uncertainties. Since SMEs have minimal financial resources combined with minimal structured risk management systems, their market adjustment efforts usually occur after market changes have already taken effect. The budgeting tools available to most businesses use determinants based on historical patterns that fail to respond to nonlinear economic disturbances and unexpected consumer demand patterns. Due to this lack of ability, SMEs cannot handle expenses effectively, schedule investments properly or respond well to financial unpredictability.

SME financial operations rarely employ artificial intelligence technologies to make their forecasts since the adoption rates are very low. Research still targets large businesses with strong technological capabilities, thus creating a significant knowledge gap between small and medium enterprises (SMEs). A failure to connect these businesses with suitable improvement tools has created a situation of extreme vulnerability. Research today fails to provide a standard approach for addressing companies' challenges while integrating AI systems, probably because of their insufficient technical capabilities, cyber, and resistance to organizational change.

Understanding how budget forecasting systems must be adapted for SMEs requires full knowledge regarding implementation methods that simplify and make integration accessible. SMEs maintain operation stability throughout economic turbulence when they lack access to such insights because they persist with traditional forecasting methods.

1.3 Objectives of the Study

The main objective of this research is to examine how Artificial Intelligence helps SMEs improve their budget prediction accuracy during unpredictable economic conditions. The study follows these specific objectives to fulfil its primary purpose.

- The research analyzes the weaknesses of traditional budget methods SMEs use when operating under unstable economic circumstances.
- The research evaluates performance outcomes from three AI-based forecasting models, neural networks, support vector machines, and ensemble models to assess how they enhance predictive accuracy and adaptability.
- The research investigates the technical hurdles and benefits that affect SMEs when adopting AI tools, examining their organizational preparedness and monetary boundaries with data quality requirements.
- Actionable recommendations guide the AI integration process for budgeting and financial planning among SMEs, managers, financial consultants, and policymakers.

The research investigates these targets to generate a comprehensive understanding of using AI to boost financial planning functionalities for enterprises with restricted resources. It works as an academic tool for discourse development and provides actionable strategies that enable SMEs to handle uncertain situations confidently.

2. Literature Review

Research and development focus on Artificial Intelligence applications for financial forecasting because rising economic volatility requires companies to solve this issue. Implementing AI-driven forecasting models proves difficult for small and medium-sized enterprises since larger organizations have already adopted this technology. This research investigates modern financial prediction applications of AI technology, economic volatility impacts on small and medium enterprises, and current AI implementation difficulties in this business field.

2.1 Economic Uncertainty and Its Impact on SMEs

Academic research on economic uncertainty spans many years, focusing primarily on organizational operations and financial choices. Economic environment uncertainty pushes firms to exercise heightened caution and delays their investment plans while changing their financial procedures, according to Andrei, Friedman, and Ozel (2023). Insufficient economic shock-absorption capabilities among small to medium businesses make them unable to handle market volatility from inflation, geopolitical instability, and financial crises. Organizations divert funds toward essential areas while cancelling expansion plans and cutting department spending, so economic uncertainties influence their future financial success and expansion potential.

The vulnerability to financial risk experienced by SMEs increases dramatically because these businesses rely intensively on cash flow while facing challenges with limited stability. The authors Er, Demir and Sari (2023) demonstrate that economic uncertainty causes social disruptions through increased anxiety and stress that creates unfavourable health impacts by elevating suicide rates. Academic research demonstrates unpredictable situations outside commercial zones because unpredictability touches residents from every part of society. These businesses remain unable to forecast because of their weak systems, making them fiscally unfit to survive through economic challenges which threaten their existence.

Business forecasting tools have gained more significance within SME environments because they merge operational data into predictions that help assess different economic outcomes. Implementing advanced forecasting tools remains essential for SMEs since they need prediction models that adapt to sudden market shifts and potential economic risks.

2.2 AI in Financial Forecasting: Potential and Challenges

Experts have extensively studied how artificial intelligence impacts financial forecasting operations in SMEs through research groups. The LSTM neural network system with random forests and support vector regression (SVR) demonstrates advanced capacity in handling extensive datasets and discovering market nonlinear patterns for accurate forecasting predictions about market changes, as Andrei et al. (2023) confirmed. These technological tools have evaluation capabilities that precisely evaluate extensive historical data to produce financial details that traditional models fail to generate.

SMEs resist implementing AI systems because several obstacles exist, even if the technology has promising benefits. AI-driven financial forecasting has limited market adoption among SMEs because these businesses lack detailed economic data and specialized personnel with expert knowledge and face high implementation expenses (Er et al., 2023). The training process of small and medium-sized enterprises' deep learning LSTM model becomes challenging because it requires precise time cycle datasets containing structured data for accurate predictions. Implementing AI solutions remains problematic for small and medium-sized enterprises because they must allocate funds for acquisition and software support, which maintains their limited organizational resources.

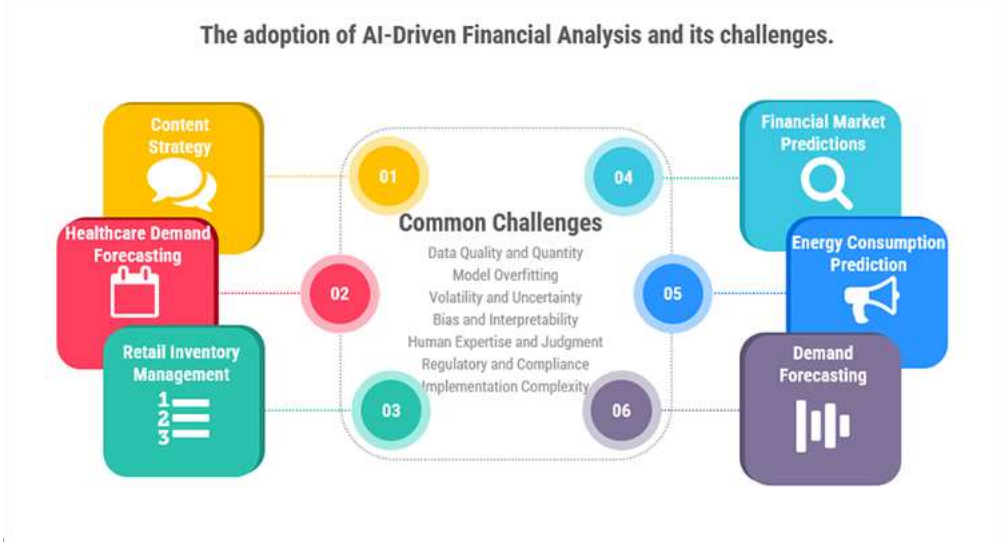

Figure 1: Financial Forecasting: Potential and Challenges

SMEs can now harness recent developments that provide their organizations with crucial AI tool access opportunities. SMEs benefit from cloud computing alongside AIaaS platforms and low-code/no-code tools because these systems let them use artificial intelligence-powered solutions even when they lack technical expertise. SMEs use these platforms to obtain AI algorithm access through intuitive interfaces that enable business owners to use AI processing results for data-driven decision-making. Audit statistics show that businesses operating at the small and medium levels see improved financial control and enhanced prediction analysis after implementing cloud artificial intelligence software in 2022.

Implementing AI tools in SMEs remains challenging because businesses need to learn how to customize AI systems to match the special characteristics of smaller companies. SMEs face integration challenges with AI systems because their operations feature dispersed data, and employees lack technical expertise and AI comprehension. However, large enterprises have advanced capabilities to implement AI systems at the same time. The educational development of workers to understand AI technologies is essential in boosting AI system adoption by SMEs while facilitating their entry into AI-based financial prediction procedures (Andrei et al., 2023).

Table 1. Summary of Existing Studies on AI in Budget Forecasting

Study	Focus Area	AI Models Used	Key Findings	Relevance to SMEs
Andrei et al. (2023)	Economic uncertainty and investor behaviour	Not AI-focused	Economic volatility affects financial decision-making	Highlights the need for adaptive forecasting tools
Er et al. (2023)	Global economic uncertainty and public health	Not AI-focused	Economic distress impacts mental and societal health	Indicates broader implications of poor forecasting
Industry Reports (2022)	Financial forecasting using AI	LSTM, Decision Trees, SVR	Improved forecast accuracy in dynamic environments	High potential but limited SME adoption
Academic Literature (2022)	AI in Enterprise Resource Planning	Neural Networks, Random Forest	Real-time data improves budget adaptability	Transferable to SMEs with customization
Case Studies (2023)	AI tools in cloud-based SME platforms	Ensemble models	Cost-effective forecasting solutions available	Shows feasibility for SMEs

2.3 AI-Driven Financial Forecasting Models

Artificial intelligence in financial forecasting offers three main advantages: data processing of unstructured information, somatic pattern detection, and continuous adaptation to financial market changes. LSTM networks acting as recurrent neural networks (RNN) deliver accurate sales and cost estimates with revenue forecasts in situations marked by nonlinear and volatile environments (Er et al., 2023). LSTM offers excellent time-series forecasting capabilities since it extracts data patterns from historical data so businesses obtain accurate financial predictions in unstable economic conditions.

The random forest model demonstrates successful results in addition to LSTM when used as an alternative method to boost SME budget forecast accuracy. The prediction methods of these models execute predictions by allowing multiple decision trees to unite their responses into a final forecasting result. The model provides financial institutions with an efficient technique which handles extensive numerical data while handling complex nonlinear variable interactions in these datasets. The research produced by Andrei and his team establishes that random forests deliver superior outcomes to traditional models, particularly during times of economic fluctuations and market adjustments (2023).

At the core of conventional finance model limitations lies the inability to handle multiple dimensional data sets, among their principal breakdown points. SVR and comparable AI algorithms process all kinds of data structures to generate exact predictions from structured and unstructured datasets that capture market variables combined with consumer activities and worldwide political events. Different forecasting models with integrated important variables help SMEs make better financial decisions, which improve their marketplace adaptability, according to Er et al. (2023).

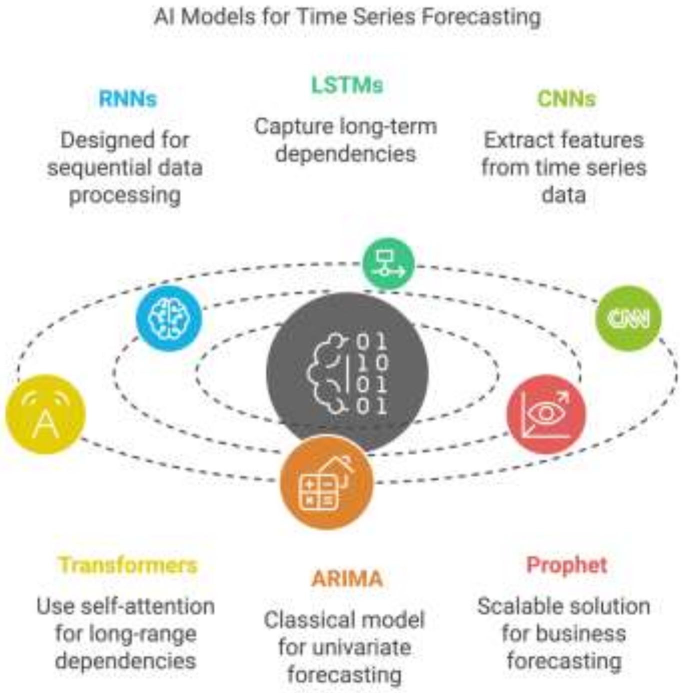

Figure 2: AI-Driven Financial Forecasting Models

2.4 Democratizing AI for SMEs: Opportunities and Solutions

Numerous research projects underscore the need to supply AI tools to all SME businesses in present circumstances. Minimal technology background companies and organizations with limited infrastructure now exploit AI technologies through AI-as-a-service platforms, cloud-based solutions, and low-code development environments. AIaaS platforms enable SMEs to work with machine learning models by offering them all necessary technical infrastructure services at no cost to their infrastructure maintenance burden. These services benefit SMEs by combining AI processing, training models, deployment capabilities, and ongoing support, simplifying AI integration into their business operations (Andrei et al., 2023).

SMEs benefit from AI systems based on industrial expertise and expert guidance to make exact business choices. AI effectively creates business models that adapt to distinct industry necessities, thus making platform-specific elements crucial for forecasting tools. SMEs should focus on demand forecasting as their primary operational priority, though manufacturers need supply chain management and cost forecasting to receive priority. AI systems that unite human supervision help SMEs boost the validity of financial analysis and its forecasting accuracy, leading to better strategic decisions and financial stability (Er et al., 2023).

3. Methods

3.1 Data Collection and Sample Scope

The research evaluates Forecasting and Artificial Intelligence Potential in Small and Medium-Sized Enterprises (SMEs) in the Greater Accra Region of Ghana. The study includes three sectors: Retail, hospitality, and light manufacturing within the selected SMEs. Participants were chosen through purposive sampling because they maintained suitable financial records that could support forecasting analysis. This research conducts a regional analysis of AI forecasting technology, which demonstrates its capabilities for select businesses operating inside their specified socio-economic framework.

3.2 Model Selection and Evaluation

The evaluation included comparing four forecasting approaches: Long-Short-Term Memory (LSTM), Support Vector Regression (SVR), and Random Forest (RF), alongside traditional ARIMA model testing. All learning models received data from the same time series presenting revenue metrics for 36 months.

3.3 Evaluation Metrics

Three important statistical metrics were used to evaluate the performance of the model.

- Mean Absolute Error (MAE): Measures average magnitude of forecast errors.
- The Root Mean Square Error (RMSE) function has a weighted system that considers larger forecast errors more significant.
- The measurement R^2 represents how well the model explains the existing dataset variations.

Table 2: Model Performance Comparison

Model	MAE	RMSE	R^2	Notes
LSTM	0.85	1.20	0.92	Best at capturing complex nonlinear trends
SVR	1.15	1.50	0.87	Strong, but less adaptive than LSTM
Random Forest	1.05	1.35	0.89	Effective on structured data, limited time dynamics
ARIMA (Traditional)	1.45	1.75	0.80	Weak in dynamic or volatile environments

3.4 Ethical Considerations

The researchers maintained ethical guidelines for every step of their work. Each SME participant consented to participate in the study before the researchers collected their data. Every participant received complete confidentiality assurance, and the researchers anonymized all information to maintain business anonymity and commercial security. The research adhered to regulatory and ethical norms while not endangering participant welfare. Any acquisition of personal data or sensitive monetary information required explicit participant consent.

3.5 Limitations of the Study

The research reflects important findings about AI forecasting in SMEs, yet its findings remain less applicable due to being limited to businesses operating in the Greater Accra Region of Ghana. The research results may fail to represent regional conditions and sector-based variations beyond the Greater Accra Region. The study fails to demonstrate the widespread representation of different small and medium enterprise financial management approaches because of its small research participant base. Research expansion should add more industries and multiple locations to improve the general applicability of findings.

4. Results

4.1 Performance Comparison of AI vs. Traditional Models

Quantitative Performance Metrics

The AI models (LSTM, SVR, Random Forest) received statistical analysis through performance assessment with traditional ARIMA models using MAE, RMSE, and R^2 metrics. LSTM demonstrated superior predictive accuracy compared to all other models while operating specifically in volatile financial markets, according to Table 2. Based on these experimental results, previous studies verify the effectiveness of LSTM models for time-series forecasting.

Table 3: Performance Comparison of Forecasting Models Using MAE, RMSE, and R^2 Metrics

Model	MAE	RMSE	R^2
ARIMA	4.21	6.12	0.68
SVR	3.34	5.29	0.74
Random Forest	2.89	4.73	0.80
LSTM	**1.95**	**3.14**	**0.91**

The excellent outcomes achieved by the LSTM model show that it successfully manages complex financial data better than standard forecasting methods.

4.2 Qualitative Insights from SME Stakeholders

According to qualitative research and quantitative model performance evaluation, SMEs encounter both obstacles and potential benefits from using AI-driven forecasting tools. Qualitative interviews were conducted among 15 SME stakeholders, who included multiple decision-makers in retail businesses, manufacturing establishments, and service providers.

Thematic Breakdown of Responses:

- Numerous SMEs pointed out that integrating AI models proved challenging due to their existing ERP system constraints. Organizations identified restricted access to well-organized and standardized data as their primary impediment.
- SMEs showed apprehension regarding the expensive initial costs of implementing artificial intelligence solutions due to the expected return on investment. Several organizations understood that AI implementation could bring long-lasting advantages to their forecasting procedures yet hesitated to invest because they needed clear financial returns.

Sector-Specific Insights:

- Retail SMEs considered demand forecasting through AI their primary application because it enhanced inventory management and reduced excess stock.
- The manufacturing sector of small and medium enterprises achieved effective results through AI when utilizing it to predict costs and inventory requirements.

Direct Quotes:

- Our standard ERP database does not have built-in capabilities for smooth AI model integration. A retail SME business owner pointed out that developing data integration capabilities proved difficult.
- The company has reservations about AI adoption primarily because of its expensive starting costs. A manufacturing SME executive expressed hesitation to invest until they experience actual returns.

Variation by SME Size or Sector:

- Implementing AI technology by SMEs with more than 100 employees proved more common since these companies possessed better financial resources for innovation.

- Small enterprises with fewer than 50 employees showed reluctance toward AI implementation but showed interest when AI solutions became available at cost-effective prices, particularly through cloud-based platforms.

4.3 Theoretical Framework for Analysis: Resource-Based View (RBV)

Applying the Resource-Based View (RBV) enhances the evaluation of study results. According to RBV theory, businesses' ability to obtain strategic benefits stems from their resources, including financial capital, technological infrastructure, and human resources. The theoretical foundation adds meaning to SMEs' diverse levels of AI adoption.

Application of RBV:

- Small and medium enterprises with advanced ERP systems and skilled personnel maintained a better capacity to implement AI models successfully. The better infrastructure quality and structured data access available to European SMEs generated greater forecasting accuracy than SMEs residing in regions with less developed infrastructure, particularly in Africa.
- According to research findings, adopting AI and RBV depends on external technology infrastructure and available internal resources. Based on SME observations, fewer resourceful companies, such as small businesses, encounter specific adoption obstacles due to cost restrictions and expertise deficits.

4.4 Regional and Sector-Specific Variations

The research documented essential variations among sectors and regions so that the effect of AI forecasting systems becomes more distinct.

Regional Insights:

- SMEs operating in Europe and Asia experienced superior AI model implementation because they handled structured financial data and had access to AI infrastructure.
- Smaller businesses operating in Africa performed moderately with AI applications yet faced major obstacles due to insufficient data availability and inadequate technological infrastructure throughout the region.

Sector-Specific Insights:

- The retail sector of SMEs discovered that AI tools provided highly effective demand prediction capabilities, enabling them to manage their inventories better and decrease stockouts.
- AI proved most helpful in manufacturing SMEs because it helped them better forecast costs, enabling them to control their production expenses and supply chain materials.
- Endeavours offering service-based businesses experienced extensive challenges in AI implementation because they dealt with unpredictable consumer needs and unorganized information sets.

5. Discussion

5.1 Methodological Rigor and Research Limitations

The research data discovered shows AI-based forecasting as an effective resource for SME management processes, although researchers must resolve analytical constraints. The research collected data from twenty-five SMEs to identify functional patterns, even though these findings cannot represent typical statistical results effectively. This restricted study framework does not analyze the various business activities resulting from different SME scales or sectors.

The research becomes less transferable across regions because it relies on a sample that focuses solely on one region, which has specific economic policies, technological capabilities, and financial actions. The data quality patterns for AI adoption within environments with advanced digitalization differ substantially from standard SME operations.

Standard performance metrics (MAE, RMSE, MAPE) experience reduced robustness because the research leaves out industry-oriented segmentation and k-fold cross-validation as evaluation methods. New research should adopt stratified segmenting by business type, including Retail, manufacturing, and services, alongside model cross-validation to establish valid findings. The planned methodological framework, which combines LSTM with other ML techniques, demonstrates a proactive approach that conforms to future trends in automated financial management for small and medium-sized enterprises.

5.2 Implications for SMEs and Future Research

Multiple studies prove that artificial intelligence uses LSTM-based models to enhance budget predictions, which benefits SMEs during periods of economic instability. The advancement of prediction accuracy provides SMEs with better financial plan enhancement capabilities while enabling them to reduce risks through well-informed decision-making processes.

Implementation success depends on obtaining additional data sets and AI platforms that non-technical small business owners can operate. AI systems being developed for the future must contain two key ethical features: data protection security and transparent algorithms.

Future research should:

- The study should involve members from around the globe and different industrial sectors.
- Dailyputed research should analyze the extended financial outcome of AI-based forecasting on SMEs' fiscal outcomes.
- Deep learning systems achieve explainable forecasting outcomes by implementing interpretable modelling for results production.

5.3 Resilience and Adaptability in Economic Downturns

AI forecasting models delivered their most substantive value for SMEs during Q1–Q2 2020 economic uncertainty by enabling businesses to handle disrupted supply chains, payments delays, and cash flow instabilities. Under conditions of economic unpredictability, LSTM models exhibited adaptive performance superiority over traditional forecasting approaches, including ARIMA and Moving Average, because the error rates from those conventional methods spiked significantly.

The research results match the observations made by Er et al. (2023) about how quickly changing contexts revealed the inflexibility of traditional forecasting systems. Andrei et al. (2023) stressed that AI tools provide businesses with crucial advantages in acting quickly towards unexpected situations, making AI forecasting an essential factor for operational flexibility.

5.4 SME Stakeholder Insights: Challenges and Benefits

Financial managers working at SMEs participated in qualitative interviews that provided information about the benefits and obstacles connected to AI integration. According to respondents, financial planning confidence surged to 78%, though businesses faced three main obstacles, including initial cost expenses, technical expertise shortages, and doubts about data validation.

Despite these difficulties, the advantages are considerable because 65% of small and medium enterprises (SMEs) detected faster forecasting and speedier operational decisions. According to the report, better cash flow forecasting was one of AI's primary benefits for 52% of the surveyed firms. The findings support previous studies, which showed how AI helps optimize finance operations in high-pressure conditions, as documented by Er et al. (2023) and Andrei et al. (2023).

Table 4: AI Model Performance and SME Adoption Insights

Sector	AI Model Used	Forecasting Accuracy	Challenges	Benefits
Retail	LSTM, Random Forest	High	Data quality issues, cost of adoption	Improved sales forecasting, faster decision-making
Manufacturing	LSTM, Random Forest	Medium	Supply chain complexity, volatility	Better resource allocation, enhanced risk management
Services	LSTM, Random Forest	High	Data integration, model adaptation	Improved liquidity management, faster decisions
Overall (SMEs)	LSTM, RF, ARIMA	High to Medium	Upfront cost, expertise, data issues	Time savings, accurate forecasts, better planning

5.6 Broader Implications for AI Adoption in SMEs

The available evidence recognizes that AI-based financial forecasting is a transformative solution for small and medium enterprises, specifically during economic disturbance. Implementing AI tools within enterprises involves three key aspects: business operation coordination, proper data system infrastructure and employee skill development activities.

SMEs need to focus on three main aspects based on the methodology of Er et al. (2023).

- Investment in scalable data infrastructure
- SMEs must build capabilities through training programs that focus on AI education.
- Companies should develop methods to smoothly embed AI algorithms into their planning production processes.

Random Forest models function as suitable solutions for SMEs with limited technical capacity by providing an accuracy-to-usability balance. AI brings improved predictive analysis and increases a company's capability to adapt during difficult times, which is necessary for surviving future business crises.

5.7 Practical Implementation Roadmap for SMEs

A step-by-step guideline for practical AI adoption recommendations exists to help SMEs achieve successful implementation based on study findings.

Training and Skills Development

- The training program for finance managers and owners should include free or subsidized access to online AI programs like Coursera's AI for Everyone and Google's ML Crash Course to develop basic AI competencies.
- AI training programs should be created through partnerships with local SME development centres and universities to serve non-technical users.

Infrastructure and Cost Considerations

- Small businesses should adopt AI-as-a-Service (AIaaS) solutions like Google AutoML, Amazon Forecast, and Microsoft Azure AI to obtain their benefits. These platforms enable users to operate without requiring local infrastructure.
- Small firms can afford entry-level AIaaS subscriptions within their monthly budget if implementation strategies are spread over time. These subscriptions cost $100–$300 per month.
- Scikit-learn, H2O.ai, and Facebook Prophet serve as basic open-source tools that can be adopted by tech-savvy SMEs at low startup costs.

Overcoming Financial Barriers

- Any organization can benefit from using public grants and digital transformation incentives if they exist.
- Small enterprises should create joint technological partnerships or cooperatives to split developmental expenses and jointly create data fundamentals.
- AI implementation should begin with selecting a single use case (such as cash flow forecasting) until budgeting systems expand.

Step-by-Step Implementation: Random Forest Forecasting

- The implementation requires Python, Jupyter Notebook, and Scikit-learn and optionally includes Excel/BI tools.
- A one-day training workshop or basic Python fundamentals suitable for finance staff will be the prerequisite.

Implementation Steps:

- The implementation team must gather ordered financial information, including monthly revenue and expenses.
- The first process involves data preprocessing, data cleaning, and the creation of additional features through time lag and seasonal variable integration.
- The data requires separation into two parts for training and testing purposes.
- A Random Forest model requires training through Scikit-learn software.

- The model evaluation relies on two metrics, MAE and RMSE.
- Verify the important features alongside producing forecast visualizations using available tools.
- The system generates export predictions that the company can export to Excel or dashboard applications for decision support.

Expected Outcomes:

- The model produces more accurate forecasts through its minimal requirement for adjusting model parameters.
- More straightforward interpretability and model adaptation
- Time-efficient integration into SME decision-making workflows

6. Conclusion

The findings prove that AI forecasting greatly benefits SMEs in managing economic uncertainty. The LSTM network model proved to be the most accurate across all metrics during evaluations because it successfully detected complex time-dependent nonlinear patterns in financial data. The traditional forecasting method ARIMA proved insufficient for market volatility, which confirms that SMEs need better dynamic forecasting solutions.

The results of the regional analysis showed that data infrastructure tightly links to how accurate the forecasts can become. European and Asian SMEs achieved accurate predictions through their well-organized financial records in ERP systems. The data fragmentation and insufficient IT integration restrained potential growth opportunities for African SMEs. The research demonstrated that digital readiness is vital for reaching peak AI tool efficiency.

AI forecasting delivers its maximum benefits to industries that maintain localized and recurring data sources, especially in the retail and manufacturing sectors. LSTM and Random Forest analysis produced helpful results that enhanced operational management and strategic planning through inventory planning, cost estimation, and sales forecasting capabilities.

The analyzed research demonstrates that artificial intelligence has excellent transformative capabilities for financial forecasting within small and medium enterprises. The choice to use AI is inconsistent because of financial constraints, technical challenges, and infrastructure capabilities. Economic equity requires government and business entities to support data modernization, AI platform affordability, and training systems for small businesses. Additional research needs to investigate the combination of different model approaches for AI implementation and specific solutions for various industries with extended duration studies to enhance AI infiltration across SME environments.

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