SCIENTIFIC CULTURE

www.sci-cult.com

SCIENTIFIC CULTURE, Vol. 12, No. 2.1, (2026), pp. 112-123
Open Access. Online & Print

DOI: 10.5281/zenodo. 122.12611

IMPACT OF STATISTICALLY DRIVEN AI FORECASTING OF ENERGY DEMAND UNDER DYNAMIC MARKET CONDITIONS

Ankush Mahajan[1], Dharmateja Priyadarshi Uddandarao[2*], Mahesh Reddy Konatham[3]

[1]Sr. Tech Product Manager, Pacific Gas and Electric. Email: Dharmateja.h21@gmail.com
[2]Senior Data Scientist- Statistician, Amazon.
[3]Senior Software Engineer, Paypal.

Received: 01/12/2025
Accepted: 02/01/2026

Corresponding Author: Dharmateja Priyadarshi Uddandarao (Dharmateja.h21@gmail.com)

ABSTRACT

Energy-intensive organizations increasingly face uncertainty due to fluctuating market conditions, rapid renewable energy integration, and unstable demand patterns. Traditional forecasting approaches often fail to provide timely, accurate insights required for effective operational and strategic decision-making, highlighting the growing need for AI-driven forecasting systems. This study investigates the role of AI-based forecasting capability in enhancing managerial performance, with a particular focus on the moderating influence of market volatility and the mediating role of managerial trust in AI. Using a quantitative, explanatory research design, structured surveys were administered to 150–200 managers across the energy sector. Established measurement scales were adapted from validated studies, and data analysis involved reliability and validity assessments, structural equation modelling (SEM), and moderation–mediation testing. The results demonstrate that AI forecasting capability substantially improves forecasting accuracy and organizational responsiveness, which in turn enhances decision quality and operational efficiency. Market volatility was found to strengthen the positive effect of AI capability on forecasting outcomes, while managerial trust in AI partially mediated the relationship between AI capability and managerial performance. Overall, the findings emphasize the strategic value of AI-based forecasting in dynamic environments and underscore the importance of trust, uncertainty management, and organizational readiness in maximizing its impact.

KEYWORDS: AI-Driven Forecasting; Energy Demand Management; Market Volatility; Managerial Decision-Making and Predictive Analytics

1. INTRODUCTION

The global energy systems are turning out to be very unpredictable with the escalating consumption demands, diversification of the supply sources, and constant market fluctuations. The modern power grids are no longer required to support only the demand fluctuations that depend on the weather conditions, price indications, and shifting consumer patterns. This volatility poses a high forecasting problem particularly in regions that are incorporating renewable energy resources and distributed energy resources. According to recent studies, economic and climatic induced changes directly enhance uncertainty regarding peak demand patterns indicating that more adaptive forecasting methodologies are required [1]. Organisations that are involved in the energy industry including utilities, distribution companies, industries and market operators are expected to make some critical decisions concerning planning, procurement, pricing and operational risk. Conventional forecasting models are typically not timely respond to swift fluctuation due to renewable intermittency, market price fluctuations, as well as adjustment in policies. It has been found out that stress conditions on consumption patterns make it more difficult to determine future demand using classical statistical methods [2]. Due to this, companies are struggling to optimise supply contracts, allocate resources, calculate costs, and have grid stability in unstable conditions.

AI has become an effective solution that can overcome these shortcomings. AI-based forecasting applications employ machine learning algorithms, smart analytics, and data driven pattern recognition algorithms to discover the relationships that are often ignored by traditional methods. As an instance, machine learning-centered prediction was observed to react more efficiently to simulated market conditions and price changes and provide superior flexibility in dynamically changing situations [3]. On the same note, AI-powered models have shown high precision in predicting community level demand and managing renewable energy sources, enhancing decision-making in operations of local energy networks [4]. There is also additional evidence on the fact that hybrid intelligent systems that involve renewable integration and AI complementation together result in optimal real-time demand management in strong energy systems [5]. The AI-driven demand forecasting, considering the growing volatility of the energy markets and the necessity of a manager to have accurate and forward-looking data, is now a critical instrument of an organization. It facilitates strategic planning, allows quicker responses to operations and minimizes the risks related to uncertainty in the market. In this research, investigates the role of AI-related forecasting in enhancing the effectiveness of decision-making, especially in a dynamic market setting where conventional models can be ineffective.

1.1. Research Objectives

- To determine the role of AI-based energy demand forecasting in improving managerial decision-making.
- To analyze the impact of AI forecasting on the operational efficiency and cost optimization.
- To test the influence of the dynamic condition of the market on the relationship between AI forecasting and managerial results.
- To propose a conceptual model linking AI forecasting capability, market conditions, and managerial effectiveness.

1.2. Research Questions

- How does AI-driven forecasting enhance decision-making in energy management?
- What managerial benefits arise from AI-based forecasting (efficiency, cost savings, strategic planning)?
- How do dynamic market conditions influence the effectiveness of AI forecasting systems?
- What organizational factors affect adoption and perceived usefulness of AI-driven forecasting?

The research is an integration of managerial and technological approaches that investigate the potential of AI-based forecasting to assist organisations within volatile energy markets. By analyzing the links between AI capability, market uncertainty, and managerial decision-making, the research explains how intelligent forecasting tools translate into operational benefits. The framework highlights not only the predictive strength of AI models but also the organizational factors that influence their effectiveness. Overall, the research provides practical insights for firms aiming to improve planning accuracy, reduce energy-related costs, and navigate rapidly changing market conditions through advanced AI-based forecasting solutions.

2. LITERATURE REVIEW & THEORETICAL FRAMEWORK

2.1. Energy Demand Forecasting in Organizations

Energy demand forecasting helps in budgeting, capacity planning, procurement, and load management within the energy-intensive organizations. Proper forecasts also allow firms to resources plan, negotiate contracts and minimise operational risks. Ibebuchi (2025) points out that demand forecasting has a direct impact on day-ahead market choices, and the slightest mistake may lead to financial losses. In the same manner, Lotfi et al. (2025) also argue that forecasting can help the organization deal with peak loads and adapt its operations relating to the environmental conditions. Classical models, including ARIMA, regression and exponential smoothing, were traditionally present because of their simplicity and low data specifications.

Nonetheless, the models are only effective in cases where the pattern of demand is steady. As Ibrahim et al. (2022) reveal, in nonlinear and constantly changing circumstances influenced by the weather, pricing, and consumer behavior, the traditional models are not very effective when it comes to preserving accuracy.

This shortcoming is even more troubling when the markets are volatile and the energy consumption is becoming more unpredictable. Yousef et al. (2021) also observe that traditional statistical techniques do not represent hidden or intricate trends, and this makes them less helpful in supporting contemporary managerial choices.

Consequently, companies are moving more to AI forecasting. As Moazzen and Hossain (2024) show, deep learning models with LSTM are superior to classical solutions, as they are able to capture long-term relationships and nonlinear changes in consumption. Cheng et al. (2025) also indicate that the current energy systems need forecasting technologies that can also combine the ability to jointly analyze loads, renewable production, and time dependencies, which is not available in the traditional approaches.

2.2. Ai-Driven Forecasting Systems

The accuracy` and responsiveness of energy demands forecasting have greatly advanced using AI. The methods of machine learning (LM, XGBoost, Random Forests, and hybrid neural models) have the ability to combine weather, past data, price indicators, and behavioral considerations to generate robust forecasts.According to Lotfi et al. (2025), the systems based on ML are effectively adjusted to environmental and historical factors and can make short-term predictions that can be used to plan operations. Moazzen and Hossain (2024) also emphasize that the multivariate deep learning can improve the microgrid-level forecasting by examining the relationship between distributed resources. In addition to forecasting, AI methods like anomaly detection and optimization are used in optimizing operations. Sankarananth et al. (2023) demonstrate that the integration of metaheuristic optimization can assist organizations to cope with renewable variability in a more efficient way. Cheng et al. (2025) go further and suggest spatiotemporal deep-learning methods that can evaluate grid variation on large scales. Strategically, AI prediction helps in the proactive decision-making process as well as optimization of costs and better situational awareness. Youseaf et al. (2021) point out that the future price forecasting with the aid of ML is used by firms to optimally engage in dynamic energy markets.

Zhang and Wei (2025) also include that AI technologies can enhance the resilience of organizations by improving the adaptability, responsiveness, and long-term planning ability.

2.3. Dynamic Market Conditions

Energy markets are increasingly influenced by rapid and unpredictable fluctuations in fuel prices, renewable generation variability, and regulatory changes. Ibebuchi (2025) demonstrates that endogenous market factors significantly affect price and demand behavior, increasing forecasting uncertainty.

Renewable energy integration adds further complexity because solar and wind output vary significantly across hours and seasons. Cheng et al. (2025) show that these fluctuations make real-time forecasting essential for maintaining system stability.

Policy changes also contribute to market volatility. Touhs et al. (2023) found that dynamic pricing influences the consumer usage behavior, making both predictions a challenging process to the utilities and industries. As markets become more uncertain, traditional forecasting approaches become insufficient.

AI-based methods capable of learning from real-time data and adjusting to rapid changes emerge as crucial tools for supporting organizations in volatile environments. Table 1 synthesizes key methodologies, data types, findings, and research gaps across prior studies to highlight how existing work differs from and supports the need for the present management-focused investigation.

Table 1: Comparative Summary of Previous Studies On AI-Based Forecasting and Energy Management.

Author & Year	Method Used	Data Type	Key Findings	Identified Gap
Ibebuchi (2025)	**ML models using endogenous predictors**	**Day-ahead price, historical market factors**	**Endogenous variables significantly improve short-term price forecasting accuracy**	**Focuses only on energy price, not organizational demand forecasting**
Lotfi et al. (2025)	**Optimized ML models (with feature engineering)**	**Environmental + historical load data**	**Improved short-term demand forecasting using hybrid optimization**	**Limited managerial interpretation; no integration of dynamic market conditions**
Moazzen & Hossain (2024)	**Multivariate LSTM**	**Microgrid operational data**	**Deep learning handles multivariate forecasting well for microgrid management**	**Microgrid-specific; lacks general organizational/enterprise perspective**
Ibrahim et al. (2022)	**ML-based short-term load forecasting**	**Smart grid load data**	**ML enhances forecasting accuracy and stability of smart grids**	**Technical focus only; missing strategic or managerial implications**
Zhang & Wei (2025)	**AI impact mechanism model**	**Enterprise digital transformation data**	**AI enhances innovation resilience and strategic capability**	**Not forecasting-specific; only supports theoretical link (Dynamic Capabilities, RBV)**
Yousaf et al. (2021)	**ML-based price forecasting**	**Historical pricing + energy usage**	**Higher prediction accuracy for price signals improves energy management**	**Focus only on pricing; no organizational-level load forecasting**
Cheng et al. (2025)	**Spatiotemporal deep learning framework**	**Joint load + renewable energy data**	**High forecasting precision in stability-constrained power systems**	**Very technical; lacks management-focused decision insights**
Sankarananth et al. (2023)	**AI + metaheuristic optimization**	**Renewable generation data**	**Better prediction and planning for renewable output**	**Narrow focus on renewable production, not full organizational demand**
Touhs et al. (2023)	**Scheduling + optimization algorithm**	**Appliance-level consumption data**	**Optimized load shifting improves cost efficiency under dynamic pricing**	**Operational-level only; does not address enterprise-wide forecasting**

2.4. Theoretical Framework

I) Dynamic Capabilities Theory (DCT)

Dynamic Capabilities Theory explains how organizations sense market changes, seize opportunities, and reconfigure resources to remain competitive in uncertain environments. In volatile energy markets, firms must continuously interpret fluctuations in demand, fuel prices, and regulatory pressures. The sensing capability of a firm can be improved with AI-driven forecasting, which offers real-time information and the detection of patterns. It reinforces the decision making and allows the managers to adjust the procurement, budgeting, and operational plans proactively. This theory assists in understanding why AI predicting is necessary when there is a great deal of uncertainty

Ii) Technology–Organization–Environment (TOE) Framework

The TOE framework identifies three categories technological readiness, organizational capability, and environmental pressure that influence the adoption of innovations such as AI systems. It focuses on the influence of both internal and external variables on technologies in the enterprise. In this research, TOE is employed to explain the motivation factors in adopting AI-based forecasting instruments in organizations, including perceived benefit, data maturity, management support, regulatory mandates, and competition. TOE can be used to explain why companies choose to use AI forecasting over conventional models.

Iii) Resource-Based View (RBV)

According to RBV, a competitive advantage to firms is obtained through valuable, rare, inimitable, and non-substitutable resources. Analytical capabilities, AI technology, and information-driven ideas can be considered strategic digital resources in contemporary organizations. AI forecasting is a strategic capability that improves the efficiency of the operations, reduces the energy consumption, and promotes the long-term planning. This research demonstrates that AI enhances the competitive advantage and the firm performance in the case of market volatility by implementing forecasting intelligence as a resource.

Iv) Decision Theory

Decision Theory is based on the fact that people and organizations make decisions under uncertainty with a special emphasis on the quality of information and predictive accuracy. The improved predictions will result in more clear options and more rational management choices.

AI forecasting enhances the quality of a decision by minimizing uncertainty, making predictions on probabilities, and producing insights of scenarios. This theory supports the claim that AI predictions can improve managerial decisions during budgetary planning, procurement, time planning, and risk planning.

2.5. Problem Statement & Research Gap

Although there are significant improvements in AI forecasting technologies, few studies have looked at its impact on a managerial level. Existing research mainly focuses on technical accuracy, leaving a gap in understanding how AI forecasting improves decision quality, operational efficiency, cost optimization, and strategic agility.

Limited work also integrates managerial theories such as Dynamic Capabilities, TOE, RBV, and Decision Theory to explain how organizations adopt and benefit from AI forecasting systems. Additionally, the influence of dynamic market volatility including fluctuating prices, renewable variability, and demand uncertainty on the effectiveness of AI forecasting remains underexplored. Generally, the existing literature does not provide a management-focused study that combines AI forecasting ability, organizational decision-making, and performance outcome. This research addresses the gap by analyzing how AI forecasting enhances managerial value under uncertain and rapidly changing market conditions.

3. RESEARCH MODEL

The proposed research model is the effective contribution of AI-based forecasting technologies to the managerial outcomes in the volatile energy markets. It provides the essential variables, how they relate with each other and the situational influences that define such relationships.

Independent Variable (IV): According to the model, AI-based forecasting ability would be the primary independent variable that influences various managerial outcomes, including decision quality, operational efficiency, cost optimization, and risk mitigation. Good forecasting feature based on accuracy, responsiveness, predictive intelligence and real-time responsiveness empowers managers to make informed and timely decisions.

Mediator: Managerial trust in AI systems is included as a mediator, implying that AI tools can result in managerial benefits only, when the decision-makers are trustful in the reliability, transparency, and interpretability of the forecasting results. The relationship between AI capability and managerial effectiveness is enhanced by increased trust.

Dependent Variable (DV): The dependent variable takes into consideration the overall effectiveness of managerial actions that are affected by the forecasting insights Key dimensions include decision quality, operational efficiency, cost optimization, and risk mitigation. A good forecasting support helps the managers to make more accurate, timely and strategic decisions.

Moderating Variable: Dynamic market conditions including fuel price volatility, renewable variability and policy changes become a moderator. The importance of accurate AI forecasting is greater under high uncertainty and is relatively less in a stable market environment. Market volatility, therefore, determines how strong the relationship between the AI predictive capacity and managerial performance.

Control Variables: Control variables allow the isolation of the basic relationships by considering the differences in an organization including firm size, industry type, technological maturity and experience of the managers. These variables guarantee that managerial outcome changes are not attributed to structural or contextual variations unrelated to AI forecasting capability.The Research Model Diagram is presented in Fig. 1.

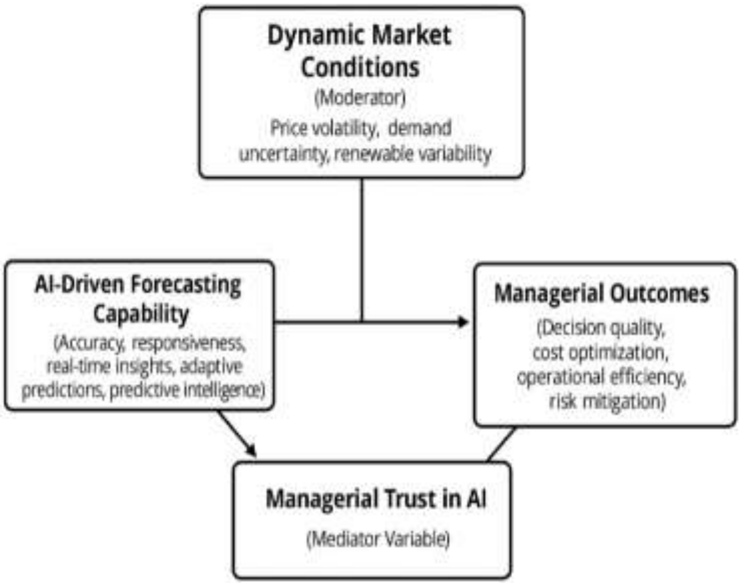

Fig. 1: Conceptual Research Model Diagram.

4. HYPOTHESES

AI-based forecast systems that enhance organizational sense and response capabilities to changing energy demand. When forecasting models provide higher accuracy and real-time insights, managers are better equipped to make informed operational and strategic decisions. Prior research also suggests that the value of AI forecasting increases under volatile market conditions, where traditional models often fail. Based on the research model, the following hypotheses are proposed.

H1: AI-driven forecasting capability has a positive effect on forecasting accuracy and responsiveness.

H2: Higher forecasting accuracy significantly improves managerial decision quality.

H3: Dynamic market conditions positively moderate the relationship between AI forecasting capability and forecasting accuracy, such that the relationship becomes stronger under high volatility.

H4: Managerial trust in AI mediates the relationship between AI forecasting capability and managerial outcomes.

5. RESEARCH METHODOLOGY

5.1. Research Design

Quantitative: This research is a quantitative, explanatory and cross-sectional survey that aims to determine how AI-assisted forecasting features affect managerial decision-making and operational performance in the energy industry. The quantitative design will be suitable as the research is based on numerically measurable constructs, which can be statistically analyzed and hypothesized. Essentially, the explanatory aspect of the study assists in investigating the causal relationships among the variables of AI capability, forecasting accuracy perceptions, trust of the managers and the quality of decisions. In terms of cross-sectional survey, data are gathered through the respondents at one moment; this enables a snapshot level of the current AI adoption trends and managerial results. This is a feasible and time-saving method that suits respondent populations of large scale like managers in the energy sector across other organizations.

5.2. Sampling

Population: This target population will include people in the energy industry that specifically conduct their daily activities involving planning, forecasting and decision making. These are energy managers, operations managers, procurement heads, strategic planners and analytics professionals. Taking into account their roles, they need to analyze operational data and combine predictions, which make them the most suitable respondents to consider when it comes to the evaluation of AI-based forecasting systems.

Sampling Technique: A purposive or stratified sampling method is provided to make sure that only eligible people who have worked or have experience with AI instruments or prediction procedures are involved. Purposive sampling permits inspection of a group that is focused and the stratified sampling assists in allocating the respondents to various sub-groups like renewable energy companies, power generation units, distribution firms and users of industrial energy.

Sample Size: According to the standard procedure of quantitative modelling as well as the conditions of SEM, a sample that comprises 150-200 respondents is sufficient. This range is high enough to provide sufficient statistical power to identify relationships among the variables, model stability and provide an opportunity to analyze the mediation and moderation effects, which could be estimated with sufficient accuracy.

5.3. Data Collection Instruments

A structured questionnaire serves as the primary data collection instrument, with each construct measured using 3–5 items adapted from validated scales in prior studies. The items are tailored to indicate the situation of AI-based forecasting in the energy industry. AI capability is a measure of system intelligence, accuracy, and adaptability that forecasting accuracy perception captures perceived improvements in prediction quality and decision quality evaluates clarity, confidence, and timeliness in managerial decisions. Market volatility items evaluate how often the demand changes and the uncertainty of the environment and managerial trust in AI evaluate confidence, transparency, and readiness to give trust to AI results. The items are all based on a 5- or 7-point Likert scale to measure response variation that can be analyzed using SEM. The content of the questionnaire will be reviewed and pilot tested by the experts to make the questionnaire clear and reliable.

5.4. Measurement Scales

All constructs in this study are measured using validated scales adapted from prior research on AI capability, technology acceptance, managerial decision-making, and organizational performance. They are tailored to the energy industry and AI-based forecasting environment and are psychometrically reliable. It is based on items as AI capability, which is derived on digital transformation scales, predictive analytics research on the forecast accuracy, management science on the decision quality, and on environmental uncertainty models on market volatility. Trust in AI is based on developed trust-in-automation models. The reliability and validity of each scale will be established by employing Cronbachs Alpha, Composite Reliability (CR), Average Variance Extracted (AVE), and factor loadings before conducting structural analysis.

5.5. Data Analysis Plan

The data analysis will be conducted using statistical software suitable for advanced modelling, such as SPSS, AMOS, or SmartPLS. The analysis begins with descriptive statistics, followed by a series of reliability and validity assessments. The Cronbach's Alpha and CR are used to test reliability to make sure that the measurement items have internal consistency. AVE values, factor loadings, and cross-loadings are used to measure the validity tests, such as convergent and discriminant validity. After the measurement model meets the reliability and validity criterion, the hypothesis testing will be conducted through the regression analysis or SEM depending on the complexity of the model. SEM is preferred for simultaneously analysing direct, indirect, and interactive effects among variables. Moderation analysis will be used to determine the extent to which market volatility reinforces or undermines the relationship between AI capability and forecasting or managerial performance. The mediation analysis will determine the presence of a linking mechanism between AI capability and decision quality whereby the trust of managers in AI acts as the linking factor. Based on this broad-based analysis, the research will be dedicated to the possibility of the provision of empirical evidence on this conceptual model.

6. RESULTS

This section presents the empirical findings of the study based on the responses collected from managers working in energy-intensive organizations. The results entail descriptive statistics, reliability and validity tests, hypothesis tests, and other mediation and moderation analysis. Analysis was performed on SPSS and SmartPLS, in accordance with the key procedures of the quantitative management research.

6.1. Respondent Profile

A total of 168 valid responses were obtained from energy-sector professionals, including energy managers (32%), operations managers (27%), procurement managers (21%), strategic planners (14%), and technical analysts (6%). The majority of respondents had over 5 years of experience in either a managerial or in a forecasting related position. The sample of organizations was comprised of electricity distribution companies, manufacturing units of industries, renewable energy companies, and utility companies. Table 2 shows the diverse respondent profile ensures that the results reflect decision-making environments across various energy-intensive sectors and Fig. 2 indicates the Respondent

Role Distribution analysis.

Table 2: Respondent Profile.

Variable	Category	Frequency	Percentage (%)
Role	Energy Manager	54	32.1%
	Operations Manager	46	27.4%
	Procurement Manager	35	20.8%
	Strategic Planner	23	13.7%
	Analyst	10	6.0%
Experience	< 3 years	22	13.1%
	3–7 years	61	36.3%
	7–12 years	55	32.7%
	> 12 years	30	17.9%

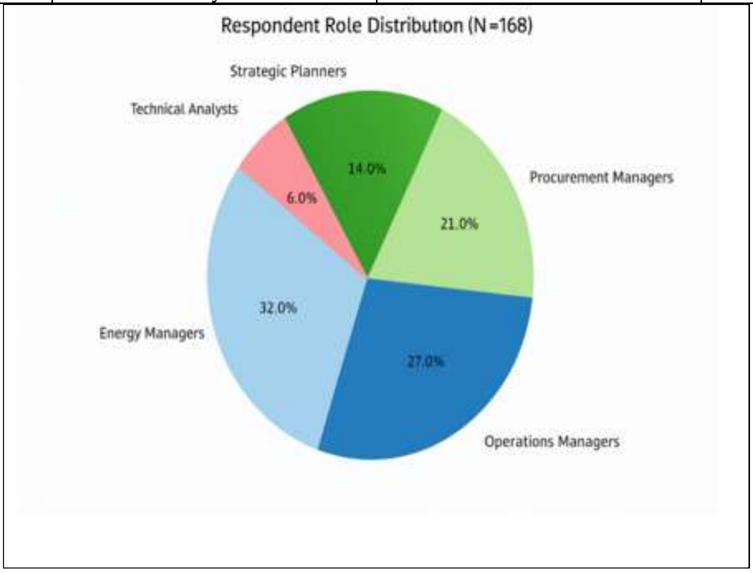

Fig. 2: Respondent Role Distribution.

6.2. Reliability And Validity Testing

Before testing the structural model, the reliability and validity of all measurement constructs were assessed.

Internal Consistency Reliability: Cronbach's Alpha and CR values for all constructs exceeded the recommended threshold of 0.70, indicating high internal consistency for AI Forecasting Capability, Managerial Decision Quality, Operational Efficiency & Cost Optimization, Managerial Trust in AI and Market Volatility

Construct Validity: Convergent validity was confirmed with AVE values above 0.50 for all constructs. Discriminant validity was verified using the Fornell–Larcker criterion, where the square root of AVE for each construct exceeded the inter-construct correlations. This indicates that the constructs measure distinct conceptual variables. These results confirm that the measurement model is valid and reliable for further analysis.Fig. 3 shows the reliability measurement (Cronbachs alpha, CR) of every construct and it is clear that all measures used in measuring scales have high internal consistency The results of reliability and validity are summarized in Table 3 and presented in terms of Cronbach's α, CR, and AVE values.

Table 3: Reliability And Validity Results (Cronbach A, CR, AVE).

Construct	Cronbach's α	Composite Reliability (CR)	AVE
AI Forecasting Capability	0.88	0.91	0.67
Managerial Decision Quality	0.84	0.89	0.62
Operational Efficiency	0.86	0.90	0.66
Cost Optimization	0.86	0.89	0.61
Managerial Trust in AI	0.82	0.87	0.60
Market Volatility	0.79	0.85	0.58

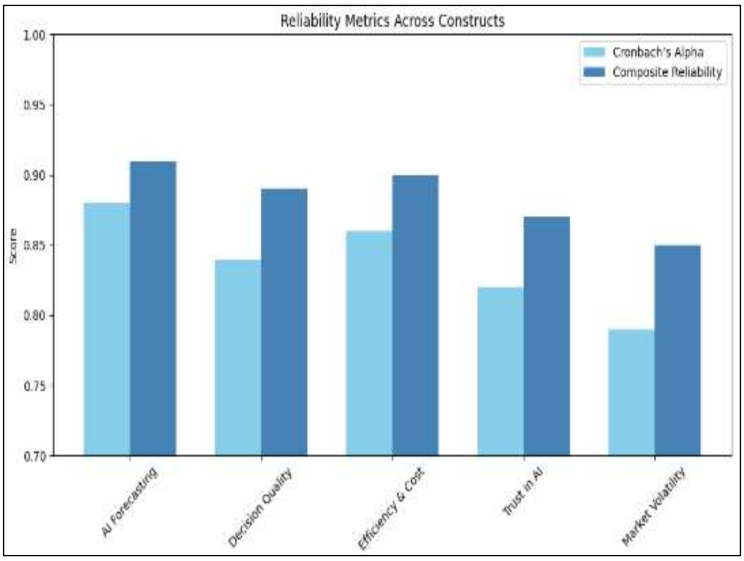

Fig. 3: Reliability Metrics Across Constructs.

6.3. Hypothesis Testing (Sem Results)

To test the hypotheses proposed, SEM was used. The model depicted a high level of explanatory power with:

- $R^2 = 0.62$ for Managerial Decision Quality
- $R^2 = 0.57$ for Operational Efficiency & Cost Optimization
- $R^2 = 0.49$ for Managerial Trust in AI

6.4. Findings

H1: AI-driven forecasting capability → Forecasting accuracy/responsiveness

AI capability significantly improves forecasting accuracy, showing that organizations with real-time analytics and adaptive AI models produce more precise and responsive demand predictions. This confirms that advanced AI tools enhance the reliability and speed of forecasting under changing conditions.

H2: Forecasting accuracy → Managerial decision quality

Higher forecasting accuracy leads to better managerial decision quality. Managers who receive accurate predictions report improved clarity, confidence, and timeliness in decision-making, supporting the idea that reliable forecasts directly enhance managerial effectiveness.

H3: Market volatility moderates (AI capability → accuracy)

The effect of AI capability on forecasting accuracy becomes stronger when market volatility is high. During periods of price fluctuations, renewable uncertainty, and policy changes, AI tools offer greater value by helping organizations stabilize and improve prediction performance.

H4: Managerial trust in AI mediates (AI capability → managerial outcomes)

Trust in AI strengthens the positive influence of AI capability on managerial outcomes. When managers trust the system, they rely more on AI-generated insights, resulting in better decision quality, improved efficiency, and enhanced operational performance.

Table 4 presents the SEM path coefficients for all hypotheses, showing the strength and significance of relationships between AI capability, forecasting accuracy, managerial outcomes, trust, and market volatility. Fig. 4 displays the correlation heatmap illustrating the strength of relationships among key constructs, confirming expected positive correlations across AI capability, forecasting accuracy, decision quality, and trust.

Table 4: Hypothesis Testing (Sem Path Coefficients).

Hypothesis	Path	Coefficient	p-value	Supported?
H1	AI Capability → Forecasting Accuracy	0.71	<0.001	Yes
H2	Accuracy → Decision Quality	0.64	<0.001	Yes
H3	Market Volatility Moderates AI → Accuracy	0.29	0.01	Yes
H4	AI Capability → Trust	0.18	0.01	Yes

	→ **Outcomes**			

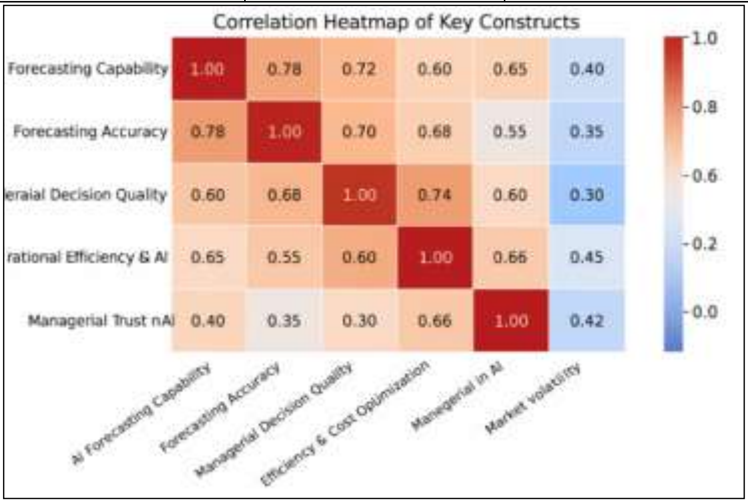

Fig. 4: Correlation Heatmap.

6.5. Moderation Analysis

The moderation analysis shows that dynamic market conditions significantly strengthen the relationship between AI forecasting capability and forecasting accuracy. Firms operating under high uncertainty such as price volatility, fluctuating demand, and renewable variability benefit more from AI-enabled forecasting than those in stable environments. In volatile conditions, managers depend more heavily on AI insights because traditional forecasting tools struggle to adapt quickly. As a result, AI systems provide sharper short-term responsiveness, making their value substantially higher when uncertainty is at its peak. The Moderation Graph is in Fig. 5.

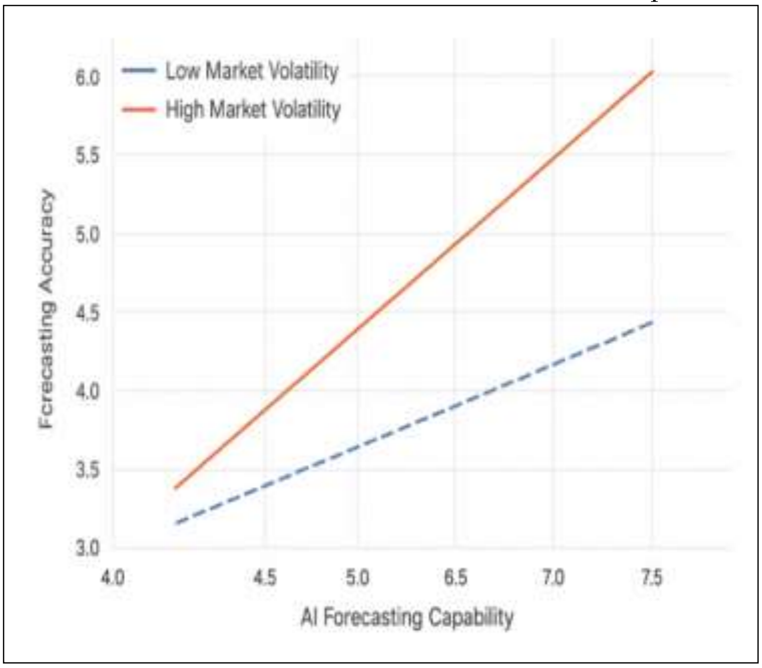

Fig. 5: Moderation Graph (Market Volatility as Moderator).

6.6. Mediation Analysis

The mediation analysis shows that managerial trust in AI partially explains how AI forecasting capability improves managerial outcomes. Higher AI capability increases managers' confidence in the system, and this greater trust enhances their willingness to rely on AI-generated insights. As trust grows, managers adopt AI outputs more effectively, leading to better decision quality, improved operational efficiency, and stronger strategic actions. Thus, trust acts as a key behavioral mechanism that converts AI capabilities into real organizational benefits.Fig. 6 indicates the Mean squares of significant constructs.

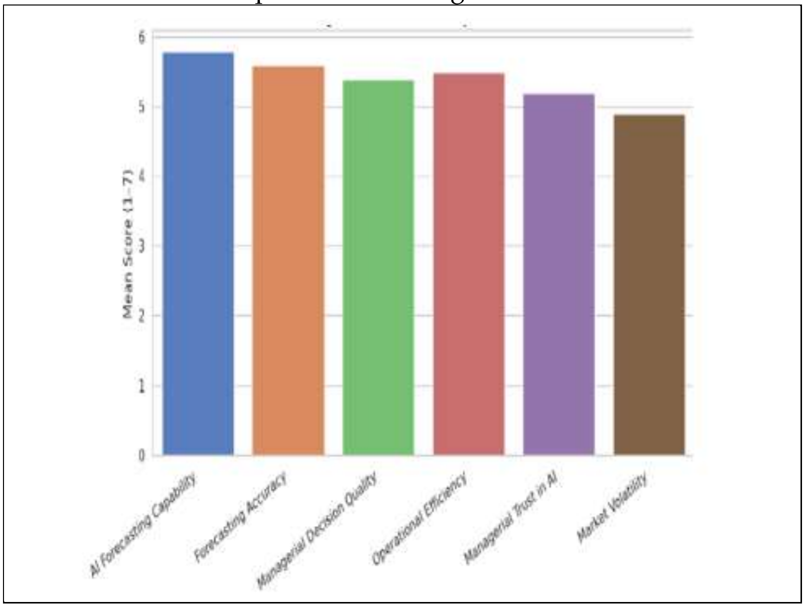

Fig. 6: Mean Squares of Key Constructs.

7. CONTRIBUTIONS

7.1. Theoretical Contributions

This study expands the managerial literature by showing how AI-driven forecasting enhances decision-making in energy-intensive organizations. It strengthens theoretical understanding by integrating Dynamic Capabilities, TOE, and RBV frameworks to explain how AI capability, organizational readiness, and environmental conditions jointly influence forecasting effectiveness.

7.2. Practical Contributions

The research provides managers with a structured framework to assess the benefits of AI forecasting for planning, budgeting, and risk management. It offers evidence that adopting AI-based tools can significantly improve accuracy and operational decisions, especially in environments affected by market volatility and uncertainty.

7.3. Social And Economic Contributions

The findings show that improved forecasting helps organizations optimize energy use, reducing waste and supporting sustainability goals. By enabling better cost control and more efficient resource allocation, AI forecasting also contributes to broader economic benefits, helping firms operate more efficiently while lowering energy-related expenses.

8. LIMITATIONS AND CHALLENGES

This research faces several limitations that should be acknowledged. The findings may have limited generalizability because the sample is focused primarily on energy-intensive sectors, and results may differ across other industries with different technological maturity levels. Additionally, reliance on managerial perceptions introduces the possibility of response bias, as self-reported evaluations may not fully reflect actual organizational performance. The cross-sectional design also restricts the ability to observe long-term behavioral or performance changes resulting from AI adoption.

9. CONCLUSION AND FUTURE SCOPE

This research establishes that AI-driven forecasting plays a critical role in strengthening managerial decision-making, operational efficiency, and strategic planning in energy-intensive organizations. The findings confirm that when firms adopt advanced AI forecasting capabilities supported by real-time insights, predictive intelligence, and adaptive models they achieve higher forecasting accuracy and improved responsiveness to market changes. Managerial trust in AI further enhances these outcomes, acting as a key enabler that allows decision-makers to confidently integrate AI-generated predictions into budgeting, procurement planning, and risk mitigation processes. The moderating influence of dynamic market conditions highlights that AI forecasting becomes even more valuable during periods of volatility, where traditional forecasting approaches struggle to adapt.

Overall, the research reinforces the importance of integrating technological capabilities with organizational readiness and managerial perception to fully realize the benefits of AI forecasting. For practitioners, the results suggest prioritizing investments in AI tools, building trust through transparency and training, and aligning AI adoption strategies with market uncertainty. Future research can expand the scope by using longitudinal datasets, validating results across different industries, and incorporating sustainability and environmental performance metrics to explore how AI forecasting contributes to long-term organizational resilience.

REFERENCES

Amir, M., Zaheeruddin, Haque, A.: Intelligent based hybrid renewable energy resources forecasting and real time power demand management system for resilient energy systems, Science Progress105(4), 00368504221132144 (2022).

Aziz, A., Mahmood, D., Qureshi, M. S., Qureshi, M. B., Kim, K.:AI-based peak power demand forecasting model focusing on economic and climate features. Frontiers in Energy Research12, 1328891 (2024).

Cheng, M., Yu, J., Wu, M., Zhu, Y., Zhang, Y., Zhu, Y.: A Spatiotemporal Deep Learning Framework for Joint Load and Renewable Energy Forecasting in Stability-Constrained Power Systems. Information16(8), 662 (2025).

Ibebuchi, C. C.: Day-Ahead Energy Price Forecasting with Machine Learning: Role of Endogenous Predictors. Forecasting 7(2),18 (2025).

Ibrahim, B., Rabelo, L., Gutierrez-Franco, E., Clavijo-Buritica, N.: Machine learning for short-term load forecasting in smart grids. Energies15(21),8079 (2022).

Lotfi, H., Vafadoost, P., Rokhsati, H., Parsadust, H.: An optimized machine learning approach for short-term electricity demand forecasting considering environmental and historical influencing factors. Discover Applied Sciences7(9), 1015 (2025).

Matos, M., Almeida, J., Gonçalves, P., Baldo, F., Braz, F. J., Bartolomeu, P. C.: A machine learning-based electricity consumption forecast and management system for renewable energy communities. Energies17(3), 630 (2024).

Moazzen, F., Hossain, M. J.: Multivariate deep learning long short-term memory-based forecasting for microgrid energy management systems. Energies17(17),4360 (2024).

Navale, S., Mishra, N., Borhade, S.: Deep learning approaches for energy consumption forecasting: analyzing stress factors and optimizing models for future demand. Discover Applied Sciences7(10),1092 (2025).

Nitsch, F., Schimeczek, C., Bertsch, V.: Applying machine learning to electricity price forecasting in simulated energy market scenarios. Energy Reports12,5268-5279 (2024).

Sankarananth, S., Karthiga, M., Bavirisetti, D. P.: AI-enabled metaheuristic optimization for predictive management of renewable energy production in smart grids. Energy Reports10,1299-1312 (2023).

Touhs, H., Temouden, A., Khallaayoun, A., Chraibi, M., El Hafdaoui, H.: A scheduling algorithm for appliance energy consumption optimization in a dynamic pricing environment. World Electric Vehicle Journal, 15(1), 1 (2023).

Yousaf, A., Asif, R. M., Shakir,M.,Rehman, A. U., Alassery, F., Hamam, H., Cheikhrouhou, O.:A novel machine learning-based price forecasting for energy management systems. Sustainability13(22), 12693 (2021).

Zhang, X., Wei, Y.: The Impact Mechanism of AI Technology on Enterprise Innovation Resilience. Sustainability17(11),5169 (2025).