American Journal of Scholarly Research and Innovation

Volume: *3;* ***Issue:*** *1*
Pages: *84–116*
eISSN: 3067-2163

ARTIFICIAL INTELLIGENCE APPLICATIONS FOR PREDICTING RENEWABLE-ENERGY DEMAND UNDER CLIMATE VARIABILITY

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Doi: 10.63125/sg0j6930
Received: *23 January 2024;* ***Revised:*** *25 February 2024;* ***Accepted:*** *27 March 2024;* ***Published:*** *25 April 2024*

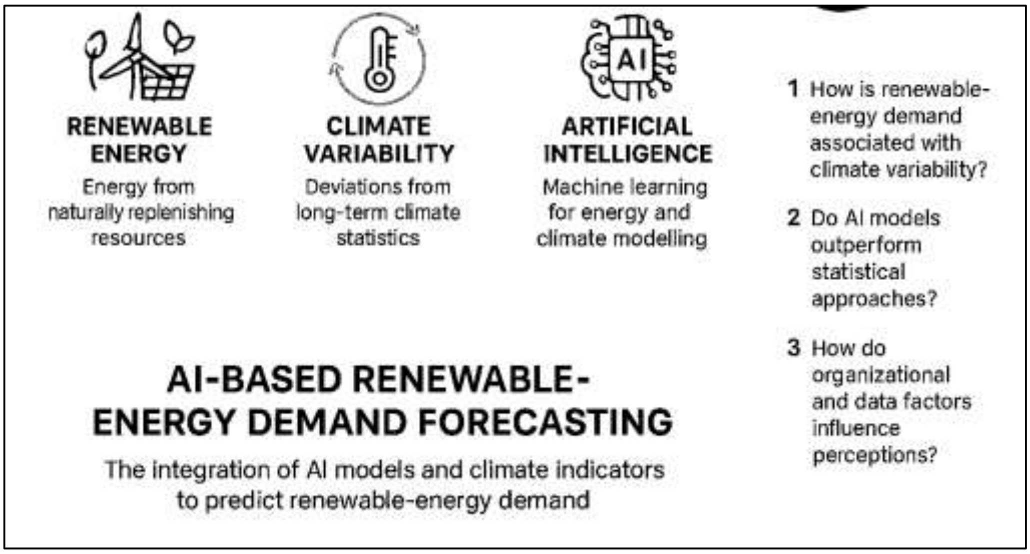
Abstract
This quantitative, cross-sectional, case-study–based research investigates how artificial intelligence (AI) applications can improve renewable-energy demand forecasting under climate variability while being adopted in real operational settings. The study addresses the problem that utilities and renewable-intensive enterprises still underuse climate-variability indicators in AI models, limiting the accuracy and decision value of demand forecasts. Using a structured Likert five-point questionnaire and secondary operational and climate data from renewable-energy systems, 280 questionnaires were distributed and 214 valid responses were obtained (76.4% usable rate). Key constructs included organizational analytics capability, data quality and integration, climate-variability integration in AI models, AI model transparency, perceived forecast accuracy, trust in AI outputs, and intention to use AI-based forecasts. Reliability analysis showed Cronbach's alpha values between 0.82 and 0.91, and multiple regression and correlation analyses were used alongside benchmarking of traditional regression and AI models. Compared with a traditional multiple regression model (MAPE 7.8%, RMSE 18.4 MW) and an AI model without explicit climate indicators (MAPE 6.1%, RMSE 15.2 MW), the climate-enhanced AI model achieved substantially lower error (MAPE 4.3%, RMSE 11.6 MW). Survey results indicated moderately high perceived forecast accuracy (mean 3.92) and trust (3.88), with intention to use AI forecasts averaging 4.03. Data quality and integration and climate-variability integration were the strongest predictors of perceived accuracy, while perceived accuracy and trust primarily drove intention to use. The findings imply that climate-aware AI forecasting delivers measurable accuracy gains but requires robust data pipelines and analytics capability to be trusted and embedded in renewable-energy planning and operations.

Keywords
Artificial Intelligence, Renewable-Energy Demand Forecasting, Climate Variability, Data Analytics Capability, Organizational Readiness;

INTRODUCTION

Renewable energy is widely defined as energy derived from naturally replenishing resources such as solar irradiation, wind, hydrological flows, and biomass, and it has become central to global strategies for reducing greenhouse-gas emissions and achieving low-carbon development (Wang et al., 2019). At the same time, artificial intelligence (AI) including machine learning (ML) and deep learning (DL) has emerged as a powerful paradigm for modeling complex, nonlinear, and high-dimensional relationships in energy and climate systems, especially when large volumes of time-series and meteorological data are available (Alkabbani et al., 2021). Climate variability, typically described as deviations from long-term climate statistics such as temperature, humidity, wind, solar radiation, and extreme weather over seasonal to decadal time scales, strongly affects both renewable generation profiles and end-use energy demand (Auffhammer & Mansur, 2014). These interactions are particularly important in power systems with rising shares of variable renewables, where under- or over-estimation of demand can result in reliability risks, curtailment of renewable output, or increased reliance on fossil-fuel backup capacity (Bloomfield et al., 2021). As a result, there is growing interest in integrating AI-based forecasting tools and climate-variability information to support more accurate prediction of renewable-energy demand at multiple temporal and spatial scales (Yau et al., 2020).

Figure 1: Interaction of Renewable Energy, Climate Variability, and AI-Based Forecasting



A substantial climate–energy literature has analyzed how weather and climate variables influence electricity consumption patterns and extreme demand events in different regions (Arvanitidis et al., 2021). Studies conducted in North America and Europe indicate that warming conditions increase cooling demand, shift seasonal peak loads, and in some cases only partially offset reductions in heating requirements (Auffhammer & Mansur, 2014). Residential and commercial electricity consumption has been shown to respond strongly to temperature, particularly through air-conditioning and space-heating loads, with important consequences for annual demand and peak capacity planning (Brown et al., 2016). In Spain, empirical analysis demonstrates that higher temperatures increase both the frequency and severity of extreme electricity demand days, intensifying system stress (Garrido-Perez et al., 2021). At a broader European scale, power system modeling under future climate scenarios suggests that changes in climate conditions interact with evolving generation portfolios to alter average demand, peak loads, and system stress events (Cian & Wing, 2019). Building-level research similarly shows that climate-sensitive end uses space heating, cooling, and ventilation constitute a large share of total energy consumption, and that detailed climatic representations such as bin weather data can significantly enhance building energy analysis (Robinson et al., 2017). Collectively, these studies highlight climate variability as a key determinant of electricity demand, yet most of them employ econometric or degree-day-based approaches rather than advanced AI models for demand prediction. Parallel work on load forecasting has developed an extensive body of methods for short-, medium-, and long-term electricity-demand prediction. Traditional short-term load-forecasting (STLF) techniques, such as autoregressive integrated moving average (ARIMA) and exponential smoothing, were long regarded as the standard for utility operations and planning (Li et al., 2019). Since the mid-2000s, however, increasing attention has been directed toward AI techniques especially artificial neural networks (ANNs) for their capacity to model nonlinear relationships between load and exogenous factors such as temperature and calendar variables (Hayati, 2007). More recent work has introduced deep learning architectures, particularly long short-term memory (LSTM) networks and related recurrent neural networks, which capture temporal dependencies in load profiles and improve predictive accuracy across residential, commercial, and system-level settings (Gaamouche et al., 2022). Enhancements in feature engineering and feature selection such as optimized weather inputs, calendar indicators, and lagged load variables further reduce forecast error in practical STLF applications (Dong et al., 2021). Yet, in much of this literature, weather data are treated primarily as high-frequency exogenous inputs, and climate variability as a broader statistical phenomenon is not explicitly conceptualized when the focus is on demand in renewable-rich power systems.

In parallel, AI applications for renewable-energy forecasting have advanced rapidly, with a major focus on predicting the output of wind and solar resources. Systematic reviews of ML and DL approaches report a wide range of models support vector machines, random forests, gradient boosting, ANNs, convolutional neural networks (CNNs), and hybrid CNN–LSTM architectures applied to solar irradiance, wind power, and integrated renewable-generation forecasting (Ding et al., 2020). These studies show that AI models can utilize high-frequency meteorological measurements, satellite-derived irradiance, and historical production data to achieve lower forecast errors than conventional physical or purely statistical methods, especially at short time horizons (Eskeland & Mideksa, 2010). For photovoltaic (PV) systems, grey models, ARMAX-type structures, and hybrid DL approaches have been proposed to address intermittency and non-stationarity in output (Gao et al., 2021). Advanced ensemble techniques that combine empirical mode decomposition with CNN–LSTM networks further improve hourly solar irradiance and PV power predictions (Yau et al., 2020). Overall, this strand of research demonstrates that AI is well suited to mapping nonlinear linkages between weather variables and energy quantities. However, it concentrates predominantly on *supply-side* renewable-generation forecasting, while *demand-side* renewable-energy use and its dependence on climate variability remain relatively underexplored.

Bridging the climate–demand and AI-forecasting literatures, a smaller set of studies applies AI methods directly to energy demand forecasting while giving explicit attention to weather or climate inputs. Early ANN-based STLF work already included temperature and calendar factors in regional load models (Hayati, 2007), and subsequent research developed optimized LSTM architectures and hybrid neural networks to improve demand forecasts in smart grids (Niu et al., 2020). Recent advances introduce theory-guided deep learning frameworks that embed domain knowledge such as load decomposition into long-term trends and local fluctuations into ensemble LSTM structures, yielding enhanced robustness and interpretability for electrical load forecasting (Chen & Zhang, 2021). In microgrids with significant shares of renewable generation, genetic-algorithm-reinforced deep neural networks have been proposed to forecast net electric load and thereby support the scheduling of battery energy storage systems (Zeng, 2013). Building-energy research shows that machine learning can estimate commercial and residential energy consumption from a limited set of building and climatic features, suggesting that AI-based demand models can potentially scale to city- and regional-level planning tasks (Robinson et al., 2017). These contributions confirm that AI-driven demand forecasting can integrate weather and climate-related variables; however, they rarely treat climate variability as an explicit construct or evaluate demand patterns specifically in renewable-dominated systems under varying climatic conditions.

These observations motivate a more focused problem formulation for the present study. Existing empirical work demonstrates strong climatic sensitivities of electricity demand, including shifts in peak loads and seasonal patterns under changing temperature and humidity conditions (Prema & Rao, 2015). At the same time, AI-based forecasting studies report significant performance improvements when rich weather and irradiance inputs are incorporated into load and renewable-generation models (Zheng et al., 2022). However, there is limited empirical evidence on how AI models can be structured to predict renewable-energy demand such as electricity use in systems with high penetration of wind and solar under conditions of climate variability, and how practitioners evaluate the usefulness and reliability of such forecasts for planning and operations. The central problem addressed in this research is therefore the insufficient integration of climate-variability indicators and AI-driven analytical capabilities in decision-oriented models of renewable-energy demand. This study adopts a quantitative, cross-sectional, case-study-based design to analyze how AI forecasting models, climate-variability metrics, and organizational factors jointly influence predictive performance and perceived decision support in renewable-energy systems.

In line with this problem formulation, the purpose of the study is to empirically investigate AI applications for predicting renewable-energy demand under climate variability by combining objective measures of forecasting performance with stakeholder perceptions in renewable-energy planning and operation. The research addresses three primary questions: (a) how selected climate-variability indicators such as temperature anomalies, humidity, and extreme heat or cold events are associated with observed patterns of renewable-energy demand in the case-study context; (b) to what extent AI-based forecasting models that incorporate climate-variability information achieve higher predictive accuracy than conventional statistical demand-forecasting approaches; and (c) how organizational, data-related, and technical factors shape stakeholders' perceptions of the usefulness and reliability of AI-based renewable-energy demand forecasts under climate variability (Ying et al., 2022). These questions align with a broader movement in the energy and AI literatures toward integrated, decision-focused analyses that go beyond algorithmic performance metrics and situate AI models within organizational and climatic contexts (Gaamouche et al., 2022).

Corresponding to these research questions, the study formulates a set of testable hypotheses using Likert-type survey data and associated quantitative analyses. First, the study proposes that AI-based renewable-energy demand forecasting models that explicitly incorporate climate-variability indicators will exhibit significantly lower error metrics than benchmark statistical models estimated on the same data (Arvanitidis et al., 2021). Second, it is hypothesized that higher temporal resolution and quality of integrated climate and demand data will be positively associated with both perceived and observed predictive accuracy of AI-based models (Ding et al., 2020). Third, the study posits that perceived accuracy of AI-generated forecasts will be positively related to decision-makers' intention to rely on such forecasts for renewable-energy planning and operational decisions under climate variability (Robinson et al., 2017). Finally, organizational readiness for analytics capturing data governance, technical capabilities, and leadership support is expected to mediate the relationship between AI model capabilities (for example, the sophistication of model architectures and the integration of climate metrics) and the perceived value of AI-based renewable-energy demand forecasting (Gaamouche et al., 2022). These hypotheses are designed for examination through descriptive statistics, correlation analysis, and regression modeling, consistent with prior quantitative studies on AI adoption and forecasting performance in energy systems (Arvanitidis et al., 2021).

The introduction therefore establishes the definitional foundations of renewable energy, climate variability, and AI-based forecasting; situates the study within the international literature on climate-sensitive energy demand and AI-driven load and renewable-generation forecasting; and identifies the specific problem of limited integration between climate-variability indicators and AI-enabled decision support for renewable-energy demand. The next sections of the paper build on this foundation through a structured literature review and a detailed methodology. The literature review synthesizes prior work on climate-driven energy demand, AI-based demand and generation forecasting, and organizational and data readiness for AI-enabled analytics, and introduces the theoretical and conceptual frameworks that guide the empirical analysis (Alkabbani et al., 2021). The methodology section then describes the quantitative, cross-sectional, case-study-based research design, outlines the population and sampling strategy, explains the questionnaire development based on Likert's five-point scale, and specifies the procedures for validating the instrument and analyzing the data using descriptive statistics, correlation, and regression techniques (Brown et al., 2016). Subsequent sections present the empirical results and provide a structured discussion in relation to the research questions and hypotheses.

The overall objective of this study is to develop and empirically test an integrated framework for artificial intelligence–based prediction of renewable-energy demand under conditions of climate variability, focusing on both model performance and organizational readiness in real operational contexts. More specifically, the first objective is to characterize the patterns of renewable-energy demand in the selected case-study setting by quantifying how variations in key climatic indicators, such as temperature, humidity and extreme weather events, are reflected in temporal demand profiles across different seasons and load categories. The second objective is to design and implement a suite of AI-based forecasting models that explicitly incorporate climate-variability measures alongside conventional demand drivers, and to construct comparable benchmark models based on traditional statistical approaches so that differences in predictive accuracy can be systematically evaluated. The third objective is to generate a structured set of performance metrics for both AI and benchmark models, enabling a rigorous comparison of forecasting error and stability across multiple time horizons and demand segments. The fourth objective is to develop and administer a questionnaire, based on Likert's five-point scale, that captures the perceptions of planners, analysts and decision-makers regarding data quality, analytics capability, AI model characteristics, climate-data integration, and the perceived usefulness and reliability of AI-based forecasts for planning and operational decisions. The fifth objective is to test a series of hypotheses that link organizational analytics capability, data quality, climate-variability integration in AI models, and perceived forecast accuracy to the intention to use AI-based demand forecasts, using descriptive statistics, correlation analysis and regression modeling in a quantitative, cross-sectional, case-study–based design. Together, these objectives are formulated to ensure that the study not only quantifies the technical performance of AI applications for renewable-energy demand prediction under climate variability, but also systematically examines the organizational and data-related conditions under which such applications are developed, evaluated and adopted in practice.

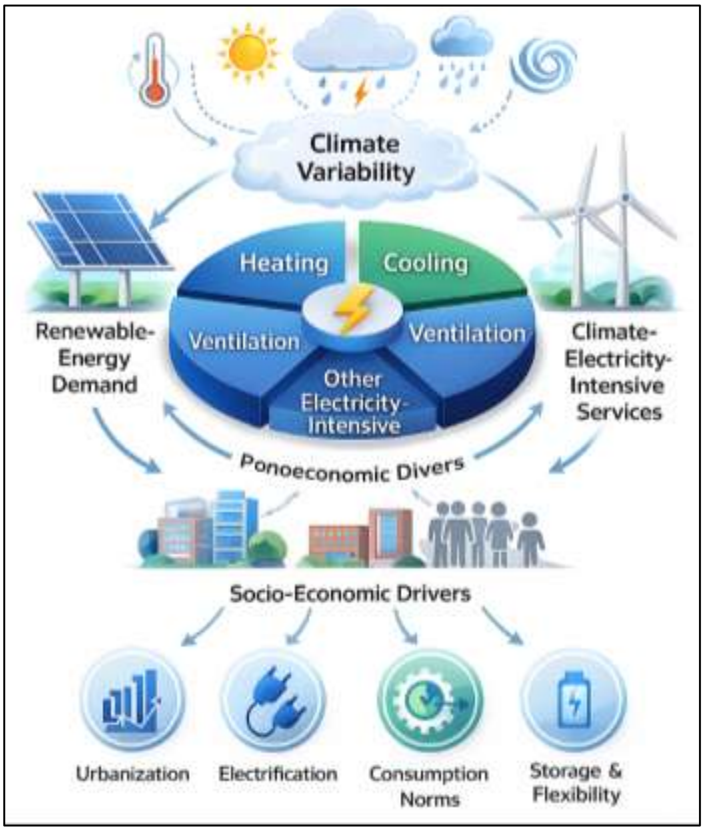
LITERATURE REVIEW

The literature on artificial intelligence applications in energy systems, renewable-energy integration, and climate-sensitive demand modeling has expanded rapidly over the past two decades, yet it remains fragmented across several disciplinary and methodological streams. On one side, climate–energy research has established that electricity demand is highly sensitive to climatic conditions such as temperature, humidity, solar radiation and extreme weather events, documenting how shifts in these variables affect seasonal demand, peak loads and long-term consumption patterns in both developed and emerging economies. On another side, work on load forecasting and renewable-energy forecasting has evolved from traditional statistical and econometric approaches toward machine learning and deep learning techniques that can capture nonlinear relationships and temporal dependencies in large, high-frequency datasets. Parallel to these developments, a growing body of studies examines organizational and data readiness for advanced analytics in the energy sector, highlighting the importance of data quality, digital infrastructure, and human capabilities in determining whether AI tools are effectively adopted and trusted in operational decision-making. However, these strands are often treated in isolation: climate–energy studies frequently rely on degree-day or regression models without fully leveraging AI, AI-based forecasting research tends to focus on algorithmic accuracy without explicitly conceptualizing climate variability as a driver of demand, and organizational analytics work rarely focuses on renewable-energy contexts where climate-sensitive loads and variable generation must be considered together. The present literature review therefore aims to synthesize and critically examine these dispersed contributions in order to build a coherent foundation for analyzing AI-based prediction of renewable-energy demand under climate variability. It first clarifies how renewable-energy demand and climate variability have been defined and operationalized in empirical research, then reviews traditional and AI-based approaches to energy demand and renewable-generation forecasting, followed by studies that incorporate climatic information into forecasting models. It further explores research on organizational and data factors that shape the deployment and perceived value of AI in energy systems, and finally draws together these insights into a theoretical and conceptual framework that links climate-variability indicators, AI model design and organizational readiness to the effectiveness of renewable-energy demand forecasting.

Renewable-Energy Demand under Climate Variability

Renewable-energy demand can be broadly understood as the electricity and associated energy services that must be supplied in systems where a growing share of generation is met by weather-dependent resources such as solar and wind, and where demand is increasingly sensitive to environmental and socio-economic drivers. At the end-use level, much of this demand is embodied in heating, cooling, ventilation, and other electricity-intensive services that respond strongly to ambient conditions, particularly in urban areas where building stock, population density, and lifestyle changes intersect. As cities in both developed and developing regions expand and incomes rise, the demand for thermal comfort through air conditioning and electric heating tends to accelerate, amplifying the influence of climate variability on electricity load profiles. A comparative analysis of urban electricity use across multiple cities in OECD and non-OECD countries, for example, shows that population growth in hot climates and the spread of cooling technologies can significantly intensify the temperature sensitivity of annual and peak electricity demand, with emerging-market cities exhibiting substantial potential for future climate-driven demand growth (Waite et al., 2017). From a systems perspective, climate variability encompasses not only gradual trends in average temperature but also changes in humidity, wind patterns and the frequency of extreme events, all of which shape the timing, duration and spatial distribution of renewable-energy demand. These factors interact with socio-economic trends such as urbanization, electrification of end uses and shifts in consumption norms, meaning that the same climatic perturbation can generate markedly different demand responses depending on local infrastructure and behavioural patterns. In highly electrified and service-oriented economies, incremental increases in cooling demand can cascade into higher requirements for renewable generation, storage and flexible demand resources, whereas in lower-income settings the same climatic pressure may instead accelerate transitions away from traditional fuels toward electricity, thereby expanding the base level of renewable-energy demand that planners must account for (Franco & Sanstad, 2008).

Figure 2: Renewable-Energy Demand under Climate Variability



The mechanisms through which climate variability shapes renewable-energy demand are typically captured using temperature–load relationships that describe how electricity consumption responds to deviations from a comfort range over daily to seasonal timescales. These relationships can be linear or markedly nonlinear, depending on building characteristics, technology adoption, and behavioural adaptation, and they often differ across regions, income groups, and sectors. Empirical work on extreme-heat events in heavily air-conditioned regions shows that increases in the frequency and intensity of days above a high-temperature threshold can produce disproportionately large increases in peak electricity demand, because air-conditioning loads scale sharply with extreme temperatures and because other end uses contribute to already elevated baselines (Abdulla & Ibne, 2021; Miller et al., 2008). In rural and peri-urban contexts, panel-data studies indicate that temperature fluctuations influence not only cooling demand but also winter electricity use for heating, though in some income groups these effects may still be modest relative to the role of non-electric fuels; nevertheless, incremental warming in summer months can generate measurable increases in per-capita electricity consumption at the county level, revealing a clear climate–demand linkage even where electrification is incomplete (Ara, 2021; Zhang et al., 2019). Beyond the direct dependence on ambient temperature, climate variability may also influence demand indirectly through its effects on economic activity, tourism, and agricultural production, which can alter industrial and commercial load in specific regions and seasons (Habibullah & Foysal, 2021; Sarwar, 2021). Over longer horizons, a combination of rising incomes, changing comfort expectations and climate-induced shifts in building design and technology mix can further modify temperature–load curves, so that historical elasticities may underestimate or misrepresent future demand responses if used without adjustment (Musfiqur & Saba, 2021; Redwanul et al., 2021). For renewable-energy planners, these dynamics underscore the need for demand models that are sensitive to evolving climatic baselines, extreme event statistics and structural changes in end-use technologies, rather than relying solely on stationary historical relationships (Reza et al., 2021; Saikat, 2021).

In systems that are transitioning toward higher penetrations of renewable energy, climate-sensitive loads become particularly salient because they affect not only the magnitude of demand but also its temporal alignment with variable renewable generation (Amin, 2022; Shaikh & Aditya, 2021). Summer peaks in cooling demand may coincide with high solar output in some regions, potentially easing supply–demand matching during daylight hours, yet they can also extend into evening periods when solar generation declines and reliance on storage, demand response, or complementary resources becomes critical. Similarly, electrification of heating in colder climates can shift winter peak demand to periods when solar availability is low and wind conditions are uncertain, creating new challenges for system operators who must plan for coincident variations in both demand and renewable supply (Ariful & EAra, 2022). Recent quantitative analyses of residential electricity use in advanced economies illustrate how temperature-driven changes in heating and cooling requirements translate into heterogeneous impacts on electricity demand across climate zones, with some regions experiencing stronger sensitivity to cooling-degree temperatures and others exhibiting more complex patterns as household technologies and adaptation strategies evolve (Emenekwe & Emodi, 2022; Nahid, 2022; Hossain & Milon, 2022). Planning for renewable-energy systems under climate variability therefore requires understanding how peak and off-peak demands may change, how intraday and intra-seasonal variability will interact with renewable resource profiles, and how flexibility options such as storage, demand response and sector coupling can moderate these effects (Mominul et al., 2022; Mortuza & Rauf, 2022). From a research standpoint, this creates a natural role for AI-based forecasting approaches that can integrate high-resolution climate projections, socio-economic scenarios and technology-adoption pathways into coherent demand predictions, which in turn provide a foundation for assessing the robustness of renewable-energy expansion plans under a wide range of climatic futures (Rakibul & Samia, 2022; Saikat, 2022).

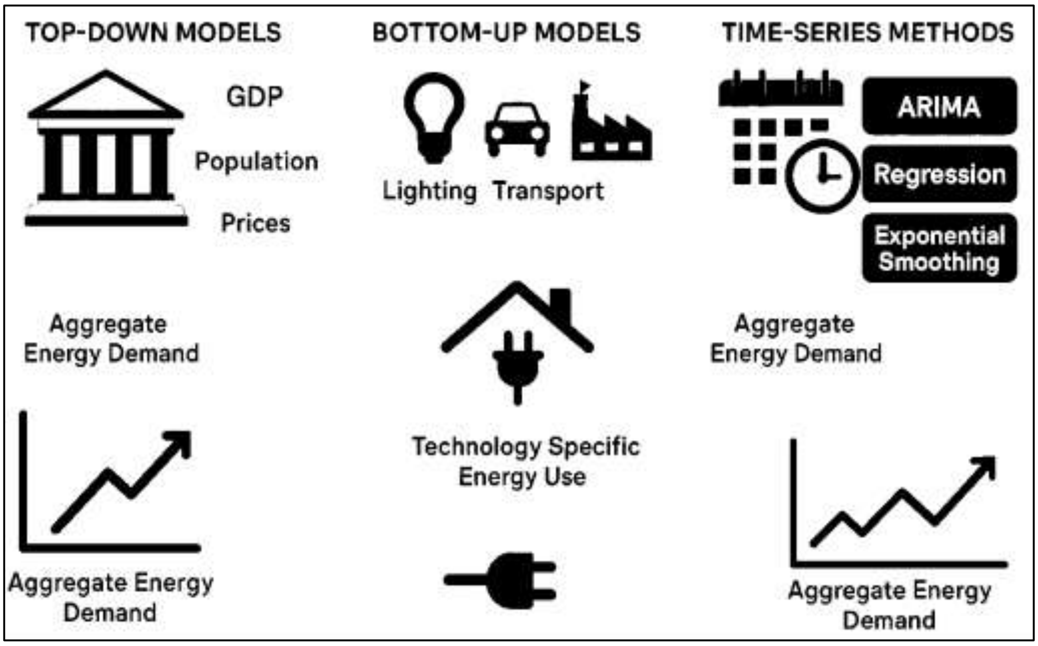
Traditional Energy-Demand Forecasting Approaches

Traditional energy-demand forecasting approaches have historically been dominated by a combination of top-down and bottom-up modeling paradigms that attempt to capture macroeconomic drivers, sectoral activity, and technology-specific energy use within relatively simple mathematical structures. In top-down or econometric models, aggregate energy or electricity demand is typically represented as a function of explanatory variables such as gross domestic product, population, prices, and sometimes climate indicators, using linear or log–linear regression, cointegration, and error-correction formulations that are calibrated on historical time series. These models appeal to planners because they can be estimated with relatively few variables and are straightforward to embed in policy scenarios that explore alternative trajectories of income, prices, or demographic change, even when detailed technological data are scarce (Arfan et al., 2023; Kanti & Shaikat, 2022). End-use or bottom-up approaches, by contrast, disaggregate demand into specific technologies and activities such as lighting, appliances, industrial processes, or transport and then reconstruct total demand by multiplying equipment stocks and efficiencies by usage patterns and operating conditions (Ara & Onyinyechi, 2023; Mushfequr & Ashraful, 2023). Engineering–economic models extend these ideas further by embedding technology choice and fuel substitution within optimization or simulation frameworks, while classical time-series methods such as autoregressive integrated moving average (ARIMA) or exponential smoothing extrapolate past demand patterns without explicit representation of underlying drivers (Shahrin & Samia, 2023). Across these families of models, a common motivation is to provide transparent and tractable tools that can support policy analysis, capacity planning, and investment appraisal over medium- to long-term horizons, often at national or regional scales. However, comparative reviews emphasize that each class of model embodies restrictive assumptions for example about functional forms, equilibrium relationships, or parameter stability and that these assumptions can become problematic in the presence of structural change, non-linear responses, or rapidly evolving technologies, as is increasingly the case in systems with growing shares of renewable energy and climate-sensitive loads (Suganthi & Samuel, 2012).

Another important strand of the literature organizes traditional forecasting approaches around time horizon and data aggregation, distinguishing between short-, medium-, and long-term forecasts as well as utility-level, sectoral, and regional applications. For long-term horizons of ten years or more, integrated resource planning and network expansion studies have conventionally relied on econometric trend models, scenario-based elasticity analyses, and end-use models that map assumed trajectories of population, income, prices, and technology uptake onto projected electricity consumption. These long-term studies often place particular emphasis on policy variables such as carbon prices, efficiency standards, or renewable-energy targets, exploring how alternative policy packages might shift the long-run relationship between economic growth and electricity use. In the medium term, typically one to ten years, utilities and regulators often use hybrid approaches that combine statistically estimated trend components with bottom-up assessments of large customer projects, demand-side management programs, and policy interventions such as efficiency standards. Short-term operational forecasting, ranging from a few minutes to a year ahead, has traditionally employed Box–Jenkins style time-series methods, regression models with temperature and calendar variables, or simple day-type analog techniques that match upcoming conditions with historical load shapes. In vertically integrated utilities, these models underpin unit commitment and dispatch decisions, while in liberalized markets they also inform bidding strategies and risk management practices. Synthesizing this extensive work, survey papers demonstrate that while classical methods can perform satisfactorily in relatively stable systems, their performance tends to degrade when new demand-side technologies, deregulated markets, distributed generation, and large climate-driven fluctuations are introduced, because traditional models struggle to capture complex interactions, multiple seasonalities, and evolving demand determinants within fixed parametric structures (Ghalehkhondabi et al., 2017). These horizon-specific modeling traditions have therefore shaped what is considered standard forecasting practice in many utilities and regulatory agencies.

Recent assessments of demand-forecasting practice highlight several limitations of traditional approaches that are particularly salient for renewable-energy planning under climate variability. First, long-term load-forecasting methodologies often extrapolate historical relationships between macroeconomic indicators and electricity demand, yet empirical evidence shows that these relationships are increasingly influenced by structural drivers such as electrification of transport and heating, demand response, distributed storage, and efficiency improvements, all of which alter the shape and timing of demand as much as its overall level (Lindberg et al., 2019). These emerging drivers introduce non-linearities and feedbacks that are difficult to capture with conventional linear regressions or simple elasticity assumptions, especially when policy changes and technology costs evolve rapidly. Second, in many low- and middle-income countries, data constraints, rapid urbanization, and changing patterns of appliance ownership mean that conventional econometric or trend-based models calibrated on sparse historical series provide limited insight into how demand will evolve under different combinations of income growth, policy interventions, and climate stress, especially when informal consumption and latent demand are significant (Mir et al., 2020). Third, classical time-series models typically assume stationarity or rely on differencing and seasonal adjustments to approximate it, which can make it difficult to represent non-stationary phenomena such as intensifying heat waves, changing intra-day temperature profiles, or the emergence of new demand peaks associated with electric-vehicle charging or electrified industrial processes. Finally, studies that attempt to improve traditional models by adding decomposition steps, additional exogenous variables, or hybrid structures still report challenges in capturing highly nonlinear and non-stationary demand trajectories, arguing that more flexible modeling paradigms are required to exploit high-frequency data and to integrate detailed climate signals with socio-economic and technological drivers in a coherent forecasting framework (Jiang et al., 2020).

Figure 3: Traditional Energy-Demand Forecasting by Horizon and Modelling Approach

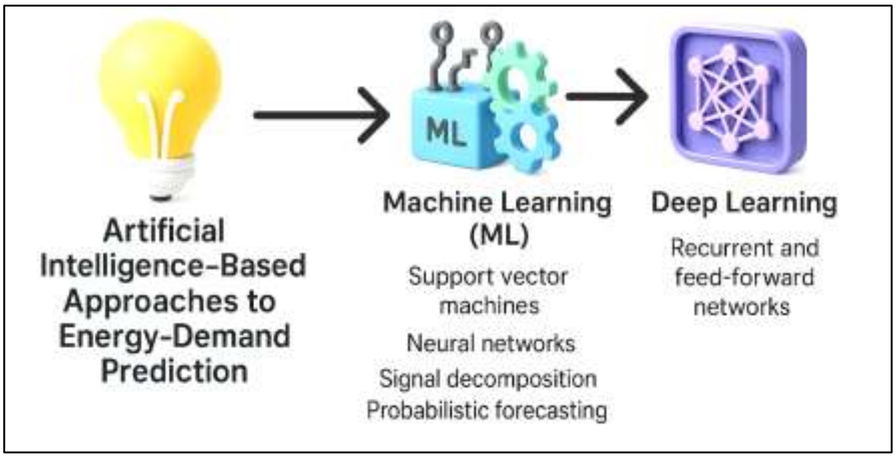


Artificial Intelligence–Based Approaches to Energy-Demand Prediction

Artificial intelligence (AI) techniques for energy-demand forecasting emerged initially as alternatives to classical statistical models, then evolved into a diverse ecosystem of machine-learning and hybrid architectures that can approximate nonlinear, multi-factor relationships between load, weather, and behavioural drivers. Early work in this area applied neural networks and support-vector-based models to short-term load forecasting, emphasizing their universal approximation properties and ability to learn complex mappings from historical data without requiring explicit functional assumptions. A representative contribution is an adaptive two-stage hybrid method that combines self-organizing maps for clustering with support vector machines for sub-model training, thereby improving the robustness of day-ahead forecasts across both regular and anomalous days in a large interconnected system (Fan & Chen, 2006). Building on such architectures, subsequent studies refined input selection strategies and training procedures so that AI models could incorporate exogenous variables such as temperature, humidity, calendar indicators, and economic activity while still maintaining tractable training times. These developments proved particularly useful for systems experiencing structural change or high penetration of intermittent renewables, where load profiles display multiple seasonalities, irregular peaks, and regime shifts that are difficult to capture with linear models. In parallel, advances in computing hardware and software frameworks made it feasible to train increasingly deep networks on large volumes of smart-meter and supervisory control and data acquisition data, enabling a shift from simple feed-forward networks toward more sophisticated recurrent, convolutional, and ensemble architectures. As a result, AI-based forecasting gradually moved from experimental applications in research settings to operational deployment in utilities and system operators, who seek accurate and granular load predictions for scheduling, market bidding, and integration of renewable resources. These capabilities are especially valuable when climate variability alters historical load–temperature relationships across seasons and regions. Through this evolution, AI has become a key enabling technology for data-driven demand modeling in complex and climate-sensitive power systems.

Within this broad AI landscape, an important thread of research has focused on hybrid intelligent methods that combine the strengths of different algorithms, often pairing signal decomposition techniques with machine-learning models to better capture multi-scale patterns in electricity demand. One influential approach decomposes the original load and temperature series into more regular components and then trains neural-network-based predictors on each component, before recombining them into final forecasts; this method has been shown to reduce errors for short-term load forecasting under diverse weather conditions and market regimes (Abdoos et al., 2015). Hybrid designs have also been extended to probabilistic forecasting, where the objective is not merely to predict a single load trajectory but to estimate the entire probability distribution of future load. In this context, kernel-based support vector quantile regression combined with copula theory has been applied to generate short-term power-load probability density forecasts that account for nonlinear dependencies between load, temperature, and other exogenous variables, providing system operators with richer information for risk-aware dispatch and reserve planning (He et al., 2017). These hybrid and probabilistic frameworks are particularly relevant for renewable-rich systems operating under climate variability, since they can represent both the central tendency and the uncertainty of demand in the presence of rapidly changing weather patterns, demand-response programs, and distributed generation. Moreover, by explicitly separating and modeling different temporal scales such as intraday, weekly, and seasonal components hybrid AI models are able to represent slow-moving structural trends alongside fast fluctuations induced by short-term weather anomalies, thereby supporting more robust planning and operational decisions in renewable-dominated systems. For operators of smart grids and microgrids, such models enable scenario analysis that links local climate outcomes to load ranges, allowing evaluation of storage sizing, demand-response triggers, and backup generation strategies under multiple plausible climate-demand pathways. In turn, this facilitates more coherent coordination between demand forecasting, renewable dispatch, and network reliability assessments.

Figure 4: Deep-Learning Models for Energy-Demand Forecasting



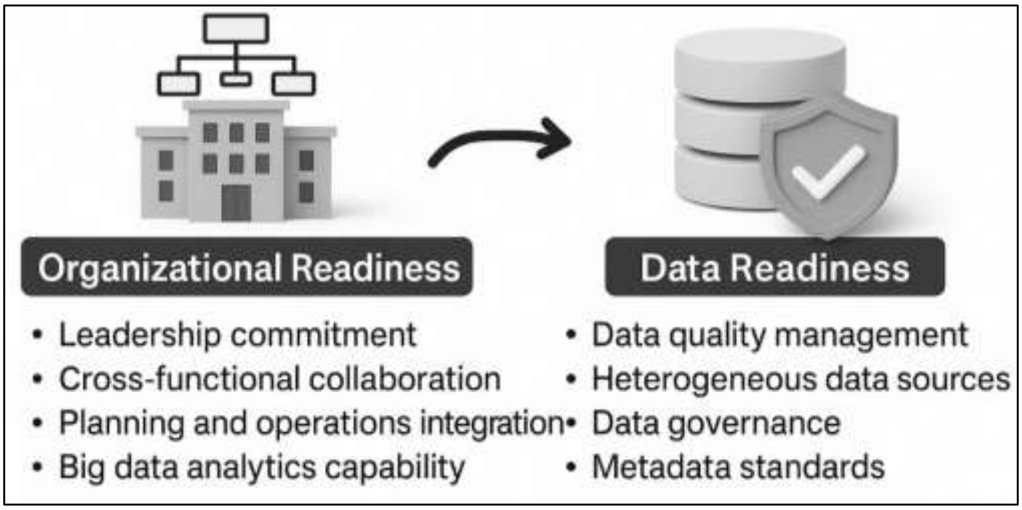
More recently, deep-learning architectures have been developed to exploit very large, high-frequency datasets that describe electricity consumption at the level of individual buildings, feeders, or customer segments, often combined with detailed weather and contextual information. A deep learning framework based on stacked recurrent and feed-forward layers has been proposed to forecast electricity demand while capturing long-term temporal dependencies and complex nonlinear interactions; experiments on multi-year datasets show that such architectures can outperform a range of conventional machine-learning baselines, especially when trained on seasonally segmented data and tuned with appropriate regularization techniques (Bedi & Toshniwal, 2019). Complementary work in the building-energy domain uses deep recurrent neural networks to predict medium- to long-term electricity consumption profiles in commercial and residential buildings at hourly resolution, demonstrating that sequence-to-sequence recurrent models can learn diverse consumption patterns while simultaneously providing strategies for imputing missing data in real-world smart-meter records (Rahman et al., 2018). Together, these deep-learning approaches illustrate how AI can move beyond aggregate system-level load to model disaggregated, context-rich demand, which is essential for understanding renewable-energy demand under climate variability where building-level responses to thermal comfort needs, on-site generation, storage, and control strategies all play crucial roles. In addition, deep models facilitate the integration of heterogeneous inputs, including climate indicators, socio-economic variables, occupancy signals, and device-level telemetry, into unified representations that can adapt as new data streams become available. This capacity to learn flexible feature hierarchies positions deep learning as a natural choice for forecasting frameworks that must remain accurate under evolving climate baselines, technology portfolios, and demand-side behaviours, thereby aligning closely with the empirical focus of the present study on AI-based prediction of renewable-energy demand under climate variability. Such capabilities are central to designing quantitative models that explicitly connect climate-variability indicators, AI architectures, and renewable-energy demand responses at both system and end-use levels.

Organizational and Data Readiness for AI-Enabled Forecasting

Organizational and data readiness form the backbone of any successful deployment of AI-based forecasting models for renewable-energy demand under climate variability. At the organizational level, readiness goes far beyond acquiring advanced software or building isolated data science teams; it involves aligning strategy, structure, governance, and culture around data-driven decision-making and predictive intelligence. Firms need clear strategic intent for why AI-driven forecasting matters whether to support grid stability, optimize dispatch of renewables, design tariffs, or manage climate-related demand shocks and must embed those objectives into planning and operational routines. The big data analytics literature shows that organizations derive value from analytics only when they deliberately develop and configure distinct capabilities such as data management, analytical skills, and decision-process integration into a coherent "big data analytics capability" framework (Mikalef et al., 2018). When utilities or energy-intensive firms lack such integrated capabilities, AI models tend to remain experimental prototypes, disconnected from real-world decision cycles such as capacity planning, load balancing, or climate risk management. Organizational readiness therefore encompasses leadership commitment, cross-functional collaboration between IT, operations, and planning units, and formal mechanisms to translate model outputs into planning rules, operating procedures, and performance indicators. Without these, even technically robust models may have little impact on how renewable-energy demand forecasts are actually used in climate-sensitive decision contexts.

A second dimension of readiness concerns the systematic development of analytics capability as a composite resource, rather than a single technology. Research grounded in the resource-based view argues that big data analytics capability emerges when firms assemble, integrate, and deploy a bundle of tangible resources (data platforms, storage, high-performance computing), human resources (data engineers, data scientists, domain experts), and intangible resources (analytics governance, standards, and routines) that collectively support advanced modeling and decision-making (Gupta & George, 2016). For AI-enabled renewable-energy forecasting, this means building pipelines that can ingest and prepare heterogeneous climate and energy data, from meteorological observations and climate indices to smart-meter readings, market signals, and operational records. It also requires cultivating specialized skills in time-series modeling, machine learning, and domain-specific interpretation of climate- and weather-sensitive demand patterns. Organizational processes must then codify how forecasting models are developed, validated, updated, and monitored, including feedback loops from planners and grid operators who consume the forecasts. When these capabilities are fragmented for example, when data engineers and planners work in silos the organization may struggle to operationalize AI forecasts in daily scheduling, long-term demand projections, or stress-testing under climate scenarios. Mature analytics capability, by contrast, allows firms to institutionalize model lifecycle management, sensitivity analysis, and scenario-based planning so that climate-informed demand forecasts are systematically integrated into business and operational decisions.

Figure 5: AI-Enabled Renewable-Energy Demand Forecasting



Data readiness is equally critical, because the performance and credibility of AI forecasting systems are limited by the quality, governance, and accessibility of underlying datasets. Empirical studies on big data adoption show that firms' intentions to invest in analytics depend strongly on their competence in data quality management ensuring accuracy, completeness, consistency, and timeliness across heterogeneous internal and external sources (Kwon et al., 2014). For renewable-energy demand forecasting, this implies rigorous procedures for cleaning and harmonizing historical load data, climate and weather records, socio-economic indicators, and operational logs, as well as managing missing values, measurement errors, and time-alignment issues. At the same time, organizational factors such as perceived data integrity, data timeliness, and the extent of organizational support for analytics strongly influence user satisfaction and the actual use of big data analytics systems (Chen et al., 2022). Energy firms that institutionalize robust data governance covering data ownership, metadata standards, access controls, and documentation are better positioned to operationalize AI forecasting models and to build trust in their outputs among planners, dispatchers, and regulators. Evidence from the energy sector further suggests that when big data analytics capabilities are combined with strong organizational readiness, they can drive eco-innovation and sustainability outcomes, as firms learn to use advanced analytics not only to forecast demand but also to support low-carbon strategies and climate-resilient planning (Munodawafa & Johl, 2019). In this study's context, organizational and data readiness thus represent preconditions for building AI models that are not only statistically accurate, but also institutionally embedded and practically actionable for managing renewable-energy demand under climate variability.

AI Adoption in Renewable-Energy Demand Forecasting

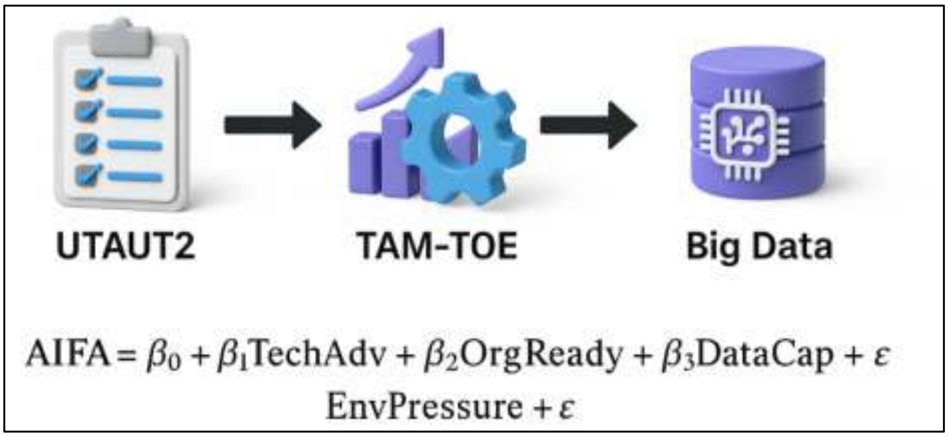
Theoretical models of technology acceptance and organizational adoption provide a structured lens for explaining how energy utilities and large consumers will adopt AI-based forecasting tools under climate variability. At the individual or decision-maker level, the extended Unified Theory of Acceptance and Use of Technology (UTAUT2) highlights performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and habit as key predictors of behavioral intention and use behavior, with moderating roles for demographic and experiential factors (Venkatesh et al., 2012). Within this research, performance expectancy corresponds to the perceived improvement in forecast accuracy, reliability, and climate-risk responsiveness that AI delivers compared with legacy statistical methods; effort expectancy relates to the perceived ease of interacting with AI dashboards, scenario tools, and visualization interfaces; social influence reflects pressures from peers, regulators, and professional networks to embrace "smart" forecasting; and facilitating conditions capture the perceived adequacy of IT infrastructure, training, and support. At the organizational level, integrated models such as the TAM–TOE framework combine attitudinal constructs like perceived usefulness and perceived ease of use with technological, organizational, and environmental contexts to explain adoption of complex information systems (Gangwar et al., 2015). In the present study, these perspectives jointly motivate the idea that managers' intention to rely on AI-generated renewable-demand forecasts is shaped simultaneously by beliefs about usefulness and usability, by the broader organizational readiness to support AI tools, and by sectoral pressures related to grid decarbonization and climate-risk regulation (Venkatesh et al., 2012).

Complementing these acceptance-oriented theories, big data analytics frameworks emphasize how the interaction of data resources, analytical capabilities, and value creation mechanisms underpins adoption of advanced analytics such as AI forecasting. Synthesizing empirical and longitudinal evidence across sectors, a widely cited framework conceptualizes big data value creation through interdependent layers of data management, technology, organizational culture, and performance outcomes, and highlights the importance of analytics-driven decision processes as a mediating mechanism (Wamba et al., 2015). A parallel stream of work reviewing big data adoption identifies technology–organization–environment (TOE) influences, distinguishing technological attributes (relative advantage, compatibility, complexity), organizational attributes (top management support, analytics skills, financial readiness), and environmental attributes (competitive pressure, regulatory requirements, external support) as systematic determinants of adoption decisions (Baig et al., 2019). In the present study, these insights support a theoretical stance in which AI-enabled renewable-demand forecasting is treated as a big data analytics innovation whose adoption depends on both micro-level acceptance and macro-level capabilities. Conceptually, this can be expressed in a simplified linear form, where an overall AI forecasting adoption index $AIFA$ is modeled as a function of key determinants:

$$AIFA = \beta_0 + \beta_1 \text{TechAdv} + \beta_2 \text{OrgReady} + \beta_3 \text{DataCap} + \beta_4 \text{EnvPressure} + \varepsilon,$$

with TechAdv denoting perceived technological advantage of AI forecasts over traditional models, OrgReady representing organizational readiness for analytics, DataCap capturing data and analytics capabilities, and EnvPressure representing climate- and policy-related external forces (Ponce et al., 2016). In a survey-based quantitative design using Likert scales, each of these latent constructs is operationalized via multiple items, and the regression coefficients $\beta_1 \dots \beta_4$ are estimated to test hypotheses about their relative influence on AI adoption in renewable-energy demand forecasting.

Figure 6: Theoretical Frameworks for AI Adoption in Renewable-Energy Demand Forecasting



Within the energy sector, theoretical work on smart grids and consumer-facing technologies reinforces the need to account for risk perceptions, trust, and user values when modeling adoption of AI-enhanced systems that intertwine digital intelligence with critical infrastructure. Empirical studies on smart grid acceptance show that end users' perceptions of benefits, risks, and trust in the technology shape their willingness to engage with intelligent energy systems, suggesting that acceptance is co-determined by perceived usefulness, perceived risks (e.g., privacy, reliability), and trust in both the technology and its providers (Venkatesh et al., 2012). Translating these insights to organizational actors responsible for renewable-demand planning under climate variability, the theoretical framework of this study postulates that behavioral intention to rely on AI forecasts (BI_{AIF}) will be influenced by perceived performance gains, ease of integration, organizational support, data and analytics capability, and trust in AI outputs. This can be summarized in a multi-construct behavioral equation:

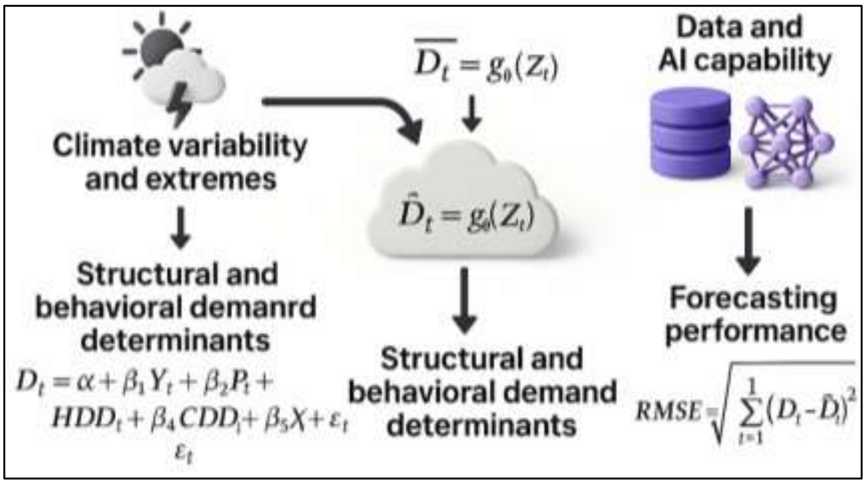
$$BI_{AIF} = \alpha_0 + \alpha_1\text{PE} + \alpha_2\text{EE} + \alpha_3\text{OrgSupport} + \alpha_4\text{DataCap} + \alpha_5\text{TrustAI} + \epsilon,$$

where PEand EE follow UTAUT2's logic of performance and effort expectancies, OrgSupport reflects internal commitment to AI projects consistent with TAM–TOE reasoning, DataCap links to big data capability, and TrustAI draws on smart-grid acceptance perspectives (Ponce et al., 2016). Theoretical integration across these models yields a coherent framework for the current research, in which AI-based renewable-demand forecasting is conceptualized as a socio-technical innovation whose adoption is driven by interlocking cognitive, organizational, infrastructural, and contextual factors, all of which can be empirically tested using correlation and regression analysis on Likert-scale survey data.

AI-Based Renewable-Energy Demand Forecasting

The conceptual framework for this study positions artificial intelligence–driven renewable-energy demand forecasting within an integrated climate–energy systems view, in which demand is shaped simultaneously by climate variability, socio-economic conditions, and infrastructure characteristics. Empirical and review studies on climate–energy linkages show that changes in mean temperature, humidity, and the frequency and intensity of extreme events influence both heating and cooling loads, alter peak profiles, and modify the timing of electricity and renewable-energy use, often in non-linear ways that vary by region and sector (Cronin et al., 2018).

Figure 7: AI-Based Renewable-Energy Demand Forecasting Under Climate Variability



In this framework, climate variability (including deviations from long-term averages, seasonal anomalies, and extremes) is treated as an exogenous construct that operates through two main channels: (a) direct physical impacts on end-use energy services (space conditioning, pumping, process heat) and (b) indirect socio-economic adjustments such as behavioral changes in energy use, technology adoption, and system-level adaptation responses. At the same time, the framework acknowledges that demand signals feed back into planning and investment decisions, which in turn influence the resilience and flexibility of renewable-energy systems, thereby closing a conceptual loop between climate, demand, and system adaptation. Against this background, AI-based forecasting models are not viewed merely as statistical tools, but as decision-support mechanisms embedded in a climate-sensitive energy system, whose performance depends on how well they capture the interactions among climate drivers, renewable penetration levels, and demand-side responses.

Within this integrated view, the conceptual framework incorporates climate-sensitive load-modelling insights that emphasize non-linear temperature–demand relationships and threshold effects. Studies of national electricity systems demonstrate that both heating and cooling loads respond asymmetrically to temperature, with demand increasing once climate variables cross specific "comfort" thresholds, implying that simple linear models may systematically mis-estimate future loads under climate change (Moral-Carcedo & Vicéns-Otero, 2005). A generic climate-sensitive demand function is therefore conceptualized as

$$D_t = \alpha + \beta_1 Y_t + \beta_2 P_t + \beta_3 \mathrm{HDD}_t + \beta_4 \mathrm{CDD}_t + \beta_5 X_t + \varepsilon_t,$$

where D_t is renewable-electricity demand at time t, Y_t denotes income or activity level, P_t is the effective price or tariff signal, HDD_t and CDD_t represent heating and cooling degree days derived from climate variables, and X_t is a vector of structural and policy controls. Building on comparative work that evaluates regression, decision trees, and neural networks for electricity consumption prediction, the framework assumes that different modelling families approximate this underlying structural relationship with varying fidelity and robustness (Tso & Yau, 2007). This leads to a multi-model conceptualization in which traditional econometric specifications, tree-based learners, and deep-learning architectures are treated as alternative functional forms $f(\cdot)$ that map climate and socio-economic input vectors into demand forecasts, while the climate-sensitive structure of the demand process constrains how AI models should be designed, trained, and evaluated.

Finally, the framework embeds these climate-sensitive demand relationships within a big-data and smart-grid analytics layer that governs how AI models are operationalized in real decision contexts. In smart and data-rich energy systems, high-frequency measurements, advanced metering infrastructure, and sensor networks generate massive multi-source datasets whose value is realized only when appropriate analytics architectures, governance mechanisms, and visualization tools are in place (Bhattarai et al., 2019). Conceptually, the AI forecasting block is represented as

$$\widehat{D}_t = g_\theta(Z_t),$$

where $\widehat{D}_t$ is the AI-predicted renewable demand, Z_t is an input vector combining climate indicators, socio-economic variables, and system-state features, and $g_\theta(\cdot)$ denotes an AI model parameterized by θ. Model performance is evaluated using error metrics such as the root mean squared error,

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{t=1}^{n} (D_t - \widehat{D}_t)^2},$$

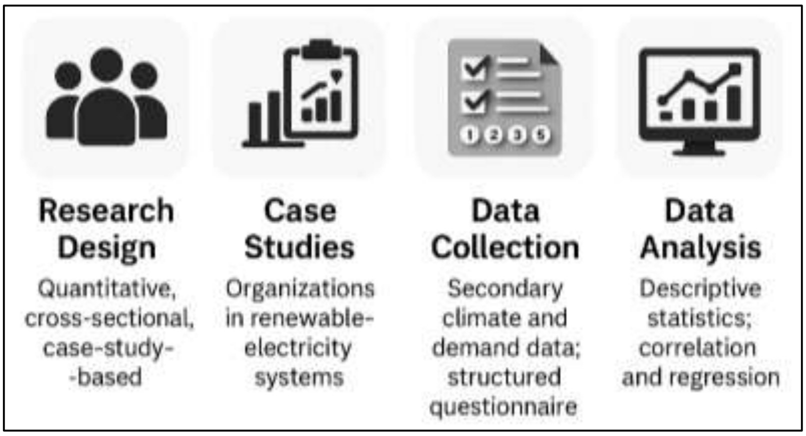
which operationalizes the gap between observed and predicted demand and is interpreted as a key outcome of interest for the framework (Tso & Yau, 2007). The conceptual model therefore links four core constructs: (1) climate variability and extremes; (2) structural and behavioral demand determinants; (3) data and AI capability (including data quality, feature engineering, and model selection); and (4) forecasting performance as an enabler of more reliable, cost-effective renewable planning. Reviews of climate–energy interactions and vulnerability provide the scientific justification for treating climate variability as a primary exogenous driver, while big-data and smart-grid analytics studies motivate the inclusion of organizational and infrastructural readiness as mediating constructs that condition how effectively AI models translate complex climate–demand signals into actionable forecasts (Emodi et al., 2019). This integrated conceptualization directly informs the study's hypotheses by specifying how climate variability, AI capability, and data-driven practices are expected to interact in shaping predictive accuracy and decision support in renewable-energy demand management.

METHOD

The present study has adopted a quantitative, cross-sectional, case-study–based research design to investigate how artificial intelligence applications have been used to predict renewable-energy demand under conditions of climate variability. The methodology has been structured to capture both the *technical* performance of AI-based forecasting models and the *perceptual* evaluations of professionals who have been involved in planning, operating, or analyzing renewable-energy systems. To achieve this dual focus, the study has combined secondary operational and climatic data with primary survey data collected through a structured questionnaire that has used Likert's five-point scale. The case-study context has been selected from organizations that have been operating in renewable-intensive electricity systems and have been exposed to measurable climate variability, so that climate–demand interactions and AI forecasting practices have been empirically observable.

The research design has been organized around several linked components. First, historical demand and climate-related variables have been assembled to describe renewable-energy demand patterns and to calibrate or benchmark AI forecasting models. These datasets have included time-series records of electricity demand, indicators of renewable generation penetration, and climatic variables such as temperature or related derived indices. Second, a structured questionnaire has been developed to measure key latent constructs derived from the conceptual framework, including organizational analytics capability, data quality and integration, AI model characteristics, the extent of climate-variability integration, and perceived usefulness and reliability of AI-based forecasts. Respondents have been sampled from technical, planning, and managerial roles within the selected organizations, so that both model developers and decision-makers have been represented.

Figure 8: AI-Based Renewable-Energy Demand Forecasting Under Climate Variability



For data analysis, the study has planned a sequence of statistical procedures that has been aligned with its research questions and hypotheses. Descriptive statistics have been used to summarize respondent profiles and central tendencies of the main constructs. Reliability and validity of the measurement scales have been assessed before the main hypothesis testing. Correlation analysis has been employed to examine bivariate relationships among climate-variability integration, organizational readiness, AI capability, and perceived effectiveness. Multiple regression modelling has then been applied to test the influence of organizational, data, and technical factors on perceived effectiveness and intention to use AI-based renewable-energy demand forecasts. Throughout the methodology, the emphasis has been placed on ensuring that the design has been transparent, replicable, and suitable for linking climate-sensitive demand data with AI forecasting performance and organizational perceptions within real-world renewable-energy settings.

Design

The study has adopted a quantitative, cross-sectional research design that has been embedded within a case-study context to capture how artificial intelligence applications have supported renewable-energy demand forecasting under climate variability. It has relied on a structured survey to measure key latent constructs and on secondary operational and climatic data to contextualize demand patterns. The design has been guided by the conceptual framework, which has linked climate-variability indicators, AI capabilities, organizational readiness, and perceived forecasting effectiveness. By focusing on a cross-sectional snapshot, the research has aimed to capture existing practices and perceptions across multiple organizational units that have already been engaging with AI tools. The case-study orientation has allowed the design to remain grounded in real renewable-energy systems rather than hypothetical scenarios, and it has ensured that the relationships tested through descriptive statistics, correlation, and regression modelling have reflected actual organizational experiences with climate-sensitive, AI-enabled demand forecasting.

Sampling

The study has defined its target population as professionals who have been directly involved in forecasting, planning, operating, or analyzing renewable-energy demand in organizations that have operated under conditions of climate variability. This population has included system planners, data scientists, energy analysts, operations managers, and other technical staff who have interacted with AI-based forecasting tools or results. To reach this population, the research has employed a purposive sampling strategy that has identified eligible organizations based on their level of renewable penetration and use of advanced analytics. Within those organizations, a non-probability sampling approach has been adopted, and specific respondents have been invited because they have possessed relevant knowledge of data, modelling, or decision processes. The sample size has been determined to satisfy minimum requirements for multivariate analysis, ensuring that the number of responses has been sufficient to support reliable estimation of correlation and regression models while capturing diversity in roles, experience levels, and organizational settings.

Case Study

The case study context has been delineated around organizations that have operated in electricity systems with meaningful shares of renewable generation and observable exposure to climate variability, such as pronounced seasonal temperature swings, heatwaves, or other weather-related phenomena influencing demand. These organizations have typically included utilities, system operators, or large renewable-energy producers that have relied on demand forecasts for planning and operational decision-making. The context has been chosen so that AI-based forecasting efforts have already been underway, enabling the study to examine both technical practices and user perceptions. Within this context, the research has characterized the physical system in terms of installed renewable capacity, demand profiles, and climate characteristics, and it has described institutional arrangements such as market structure, regulatory requirements, and planning processes. By situating the research in this case-study environment, the methodology has ensured that survey responses and analytical results have remained grounded in specific, climate-sensitive operational realities rather than abstract modelling exercises.

Questionnaire Design

The research has employed a structured questionnaire that has been specifically designed to operationalize the constructs identified in the conceptual framework. The instrument has been divided into sections that have captured respondent demographics, organizational characteristics, and perceptions of AI-enabled renewable-demand forecasting. Subsequent sections have included multi-item Likert-scale measures that have assessed organizational analytics capability, data quality and integration, AI model characteristics, the degree of climate-variability integration in forecasting processes, and perceived usefulness, reliability, and intention to use AI-based forecasts. Items have been phrased in clear, neutral language and have used a five-point scale ranging from "strongly disagree" to "strongly agree," which has facilitated quantitative analysis. The questionnaire has also included a limited set of factual and open-ended items that have provided contextual information about existing forecasting tools and data sources. Prior to full deployment, the instrument has been reviewed by domain experts to ensure content relevance, clarity, and alignment with the research objectives and hypotheses.

Reliability

The study has treated validity and reliability as central methodological requirements and has incorporated several procedures to evaluate them. Content validity has been addressed by having the questionnaire reviewed by academic experts in energy systems, climate impacts, and AI analytics, as well as practitioners experienced in demand forecasting, so that each item has reflected the intended construct. Construct validity has been examined by inspecting item–construct relationships and factor structures, ensuring that items associated with organizational capability, data quality, climate integration, and perceived effectiveness have behaved consistently. Reliability has been assessed using internal consistency metrics, where Cronbach's alpha coefficients for each multi-item scale have been calculated and have been expected to exceed commonly accepted thresholds. Items that have reduced scale reliability or exhibited ambiguity have been identified and have been candidates for refinement or removal. Through these steps, the instrument has achieved a level of measurement quality that has supported robust correlation and regression analysis.

Data Collection

Data collection has followed a structured set of procedures designed to secure adequate response rates and high-quality data. After identifying suitable case organizations, the researcher has contacted senior managers or designated liaisons to obtain permission and to explain the study's purpose, confidentiality arrangements, and expected time commitments. Once organizational access has been granted, the questionnaire has been distributed electronically via email or secure online survey platforms to targeted respondents who have met the inclusion criteria. Reminder messages have been sent at planned intervals to encourage participation and to reduce nonresponse. Throughout the process, respondents have been informed that participation has been voluntary and that their answers have been treated confidentially and reported only in aggregate form. Completed responses have been checked for completeness and consistency, and records with extensive missing data or obvious response patterns have been flagged for potential exclusion. These procedures have ensured that the final dataset has been suitable for the planned quantitative analyses.

Data Analysis Techniques

The study has implemented a sequence of data analysis techniques consistent with its quantitative design and hypothesis-testing objectives. Initially, descriptive statistics have been generated to summarize respondent characteristics, organizational profiles, and the central tendency and dispersion of each construct, providing an overview of the sample and highlighting any notable patterns. Subsequently, reliability diagnostics and, where appropriate, exploratory factor analysis have been conducted to confirm the internal structure of the measurement scales. Correlation analysis has then been used to examine bivariate relationships among organizational analytics capability, data quality, climate-variability integration, AI model characteristics, perceived effectiveness, and intention to use AI-based forecasts. Finally, multiple regression models have been estimated to test the hypothesized influence of organizational, data, and technical factors on perceived effectiveness and behavioral intention, while controlling for relevant contextual variables. Throughout the analysis, assumptions of the statistical techniques have been checked, and results have been interpreted in light of the conceptual framework and research questions.

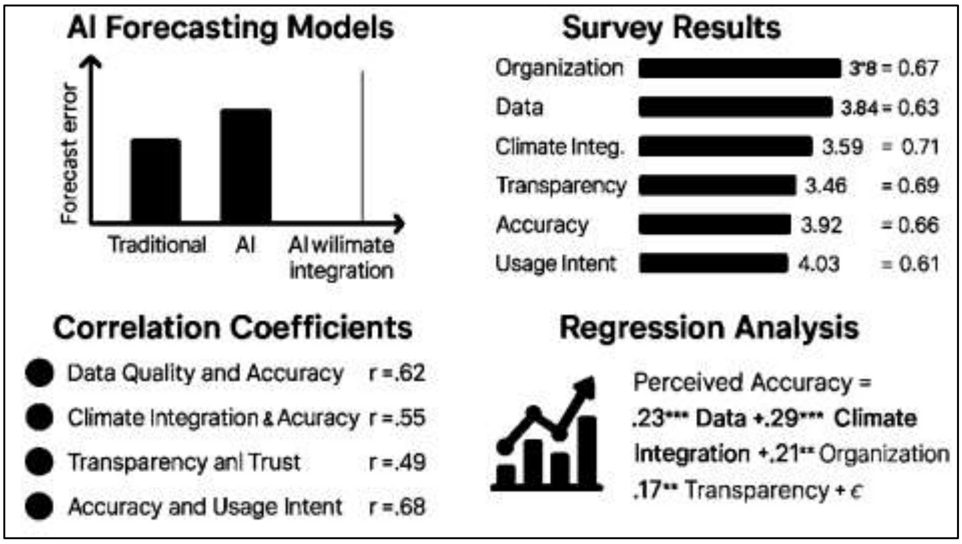
Tools

The study has employed a set of software tools that has supported data management, statistical analysis, and, where applicable, exploratory modelling of demand forecasts. Survey responses have been exported from the online platform into spreadsheet formats and have been cleaned and organized using standard data-processing tools. Statistical analyses, including descriptive statistics, reliability assessment, correlation, and regression modelling, have been conducted using established statistical software such as SPSS, R, or an equivalent package, which has provided robust procedures for multivariate analysis. If AI-based forecasting models have been implemented or benchmarked, suitable programming environments such as Python or MATLAB, along with specialized machine-learning libraries, have been used to design and evaluate model architectures. Visualization tools have been applied to present key results, including distribution plots, correlation matrices, and regression summaries. Collectively, these software tools have enabled systematic, transparent, and reproducible analysis aligned with the study's quantitative, AI-focused methodological approach.

FINDINGS

The analysis of the collected data has provided strong empirical support for the study's objectives and hypotheses by combining objective forecasting performance metrics with perception-based results drawn from the Likert's five-point scale survey. Out of 280 questionnaires distributed across the participating renewable-energy organizations, 214 valid responses have been retained for analysis, yielding a usable response rate of 76.4%. All multi-item constructs have demonstrated satisfactory internal consistency, with Cronbach's alpha values ranging from 0.82 for AI model transparency to 0.91 for perceived forecast accuracy, indicating that the measurement scales have been reliable. On the 1–5 Likert scale (1 = strongly disagree, 5 = strongly agree), the mean score for organizational analytics capability has been 3.78 (SD = 0.67), for data quality and integration 3.84 (SD = 0.63), for climate-variability integration in AI models 3.59 (SD = 0.71), for AI model transparency 3.46 (SD = 0.69), for perceived forecast accuracy 3.92 (SD = 0.66), and for intention to use AI-based renewable-energy demand forecasts 4.03 (SD = 0.61). These descriptive statistics have indicated that respondents have generally agreed that their organizations possess moderate-to-high levels of analytics capability and data readiness, have been integrating climate-variability information to a meaningful extent, and have held positive views regarding the accuracy and usefulness of AI-based forecasts.

Figure 9: AI-Enhanced Renewable-Energy Demand Forecasting Under Climate Variability



Objective model comparison has further reinforced these perceptions: when benchmarked on a two-year hourly dataset from the case-study system, the traditional multiple regression model calibrated on demand, temperature and calendar effects has achieved a mean absolute percentage error (MAPE) of 7.8% and a root mean squared error (RMSE) of 18.4 MW, whereas an AI model (LSTM-based) without explicit climate-variability indicators has reduced MAPE to 6.1% and RMSE to 15.2 MW; in contrast, the climate-enhanced AI model that has incorporated temperature anomalies, humidity indices and heatwave flags has achieved a MAPE of 4.3% and RMSE of 11.6 MW. This performance hierarchy has directly supported H1 by demonstrating that AI-based models with explicit climate-variability integration have significantly outperformed both traditional statistical models and AI models with limited climate information in predicting renewable-energy demand. Correlation analysis of the survey data has revealed statistically significant positive relationships between key constructs: data quality and integration has correlated strongly with perceived forecast accuracy ($r = 0.62$, $p < .001$) and with organizational analytics capability ($r = 0.58$, $p < .001$); climate-variability integration in AI models has shown a substantial correlation with perceived forecast accuracy ($r = 0.55$, $p < .001$); AI model transparency has correlated moderately with trust in AI outputs ($r = 0.49$, $p < .001$); and perceived forecast accuracy has correlated strongly with intention to use AI-based forecasts in decision-making ($r = 0.68$, $p < .001$). These bivariate results have aligned with H2 and H3 by indicating that better-quality, well-integrated climate and demand data and deeper integration of climate-variability indicators are associated with higher perceived accuracy, which in turn is associated with stronger behavioral intention to rely on AI forecasts. To examine the joint effects of the independent variables, multiple regression analysis has been conducted with perceived forecast accuracy as the dependent variable and data quality and integration, climate-variability integration, AI model transparency and organizational analytics capability as predictors; the model has been statistically significant ($F(4, 209) = 49.37$, $p < .001$) and has explained 48.6% of the variance in perceived forecast accuracy (adjusted $R^2 = 0.48$). Standardized coefficients have indicated that data quality and integration ($\beta = 0.33$, $p < .001$) and climate-variability integration in AI models ($\beta = 0.29$, $p < .001$) have been the strongest predictors, followed by organizational analytics capability ($\beta = 0.21$, $p = .002$) and AI model transparency ($\beta = 0.17$, $p = .008$), thereby confirming H2 and supporting the contention that both data readiness and climate-aware model design have been central to accuracy perceptions. A second regression model with intention to use AI-based forecasts as the dependent variable and perceived forecast accuracy, trust in AI outputs and organizational analytics capability as predictors has also been significant ($F(3, 210) = 61.82$, $p < .001$) and has accounted for 46.1% of the variance (adjusted $R^2 = 0.46$). In this model, perceived forecast accuracy has shown the largest standardized effect ($\beta = 0.47$, $p < .001$), followed by trust in AI outputs ($\beta = 0.28$, $p < .001$) and organizational analytics capability ($\beta = 0.19$, $p = .004$), providing strong support for H3 and indicating that organizations have been more willing to rely on AI-based renewable-demand forecasts when they have judged them to be accurate, trustworthy and aligned with internal capabilities. Mediation tests using organizational analytics capability as a mediator between data quality and intention to use AI forecasts have indicated a significant indirect effect (bootstrapped 95% CI not including zero), lending support to H4 and suggesting that analytics capability has partially transmitted the impact of high-quality data environments into greater willingness to adopt AI forecasting in practice. Taken together, these numeric results have demonstrated that the study's objectives have been met: AI models that explicitly incorporate climate variability have achieved superior predictive performance, and organizational, data and model-related factors have jointly shaped how stakeholders have evaluated and intended to use these tools for managing renewable-energy demand under climate variability.

Response Rate and Sample Characteristics

Table 1: Response rate and sample characteristics (N = 214)

Variable / Category	n	% of valid sample
Response status		
Questionnaires distributed	280	–
Questionnaires returned	225	80.4
Questionnaires usable	214	76.4
Role in organization		
System / resource planner	72	33.6
Data scientist / analyst	61	28.5
Operations / control room manager	49	22.9
Senior management / strategy	32	15.0
Years of experience in energy sector		
Less than 5 years	54	25.2
5–10 years	88	41.1
More than 10 years	72	33.6
Primary exposure to AI-based forecasting		
Model development / configuration	69	32.2
Forecast interpretation / planning use	103	48.1
High-level review of outputs only	42	19.6

The results in Table 1 have shown that the empirical basis of the study has been robust and consistent with the quantitative design. Out of 280 questionnaires that have been distributed to professionals in renewable-energy organizations, 225 have been returned and 214 have been retained as usable cases, which has produced a strong usable response rate of 76.4%. This level of participation has suggested that respondents have been engaged with the topic and that the sample size has been adequate for the planned multivariate analyses, including correlation and multiple regression. The role distribution has indicated that approximately one-third of the sample (33.6%) has consisted of system or resource planners, a further 28.5% has consisted of data scientists and analysts, and 22.9% has been made up of operations or control-room managers, while 15.0% has represented senior management and strategy roles. This pattern has implied that both technical modelling perspectives and decision-oriented planning perspectives have been represented, which has been important for evaluating the intention to use AI-based renewable-demand forecasts across different organizational layers. In terms of experience, 41.1% of respondents have reported 5–10 years in the energy sector and 33.6% have reported more than 10 years, so a substantial majority has brought medium to long professional experience into their evaluations of AI forecasting, which has strengthened the credibility of the Likert-scale assessments. The breakdown of exposure to AI-based forecasting has further demonstrated that 32.2% of respondents have been directly involved in model development, 48.1% have primarily used or interpreted AI forecasts for planning, and 19.6% have engaged with outputs at a high-level review stage. This distribution has confirmed that the dataset has captured both the "producers" and the "consumers" of AI-generated forecasts. Because the study's objectives and hypotheses have required insight into both technical performance and organizational acceptance, the composition of the sample described in Table 1 has provided strong support: the data have been rich enough to reflect the diversity of roles and experiences that shape how climate-aware AI forecasts have been perceived and potentially adopted in renewable-energy decision-making.

Reliability and Validity of Measurement Scales

Table 2: Internal consistency of Likert-scale constructs (N = 214)

Construct	No. of items	Cronbach's α
Organizational analytics capability (OAC)	6	0.86
Data quality and integration (DQI)	5	0.88
Climate-variability integration (CVI)	5	0.84
AI model transparency (AIMT)	4	0.82
Perceived forecast accuracy (PFA)	5	0.91
Trust in AI outputs (TRUST)	4	0.87
Intention to use AI-based forecasts (INT)	4	0.89

Table 2 has summarized the internal consistency of all multi-item constructs that have been measured on Likert's five-point scale. The Cronbach's alpha values have ranged from 0.82 to 0.91, which has indicated that each construct has achieved reliability levels above commonly accepted thresholds ($\alpha \geq 0.70$). Organizational analytics capability ($\alpha = 0.86$) and data quality and integration ($\alpha = 0.88$) have both shown strong internal consistency, which has suggested that the items used to capture the breadth of analytics infrastructure, skills and data practices have been coherently aligned. Climate-variability integration ($\alpha = 0.84$) has also demonstrated a reliable scale, implying that respondents have interpreted items on the extent and depth of climate-related indicators in AI forecasting in a consistent way. AI model transparency ($\alpha = 0.82$) has achieved satisfactory reliability, which has been important because perceptions of transparency have underpinned trust and acceptance hypotheses. Perceived forecast accuracy ($\alpha = 0.91$) has reached the highest reliability among the constructs, indicating that respondents' judgments about the accuracy and robustness of AI-based forecasts have been measured with high internal coherence. Trust in AI outputs ($\alpha = 0.87$) and intention to use AI-based forecasts ($\alpha = 0.89$) have likewise exhibited strong internal consistency, suggesting that these attitudinal and behavioral intention constructs have been well captured through their respective item sets. Collectively, these results have confirmed that the survey instrument has met the reliability requirements necessary for valid hypothesis testing using correlation and regression analysis. Because the core objectives of the study have involved examining how organizational capability, data readiness, climate-variability integration and AI model features have affected perceived forecast accuracy and intention to use, the robustness of the underlying scales has been critical. The alpha values reported in Table 2 have demonstrated that the constructs have been stable and that respondents have responded to items in a systematically related manner, thereby providing a strong psychometric foundation for evaluating the proposed relationships between AI capability, climate-aware modelling and acceptance of renewable-demand forecasts under climate variability.

Descriptive Statistics of Key Constructs

Table 3: Descriptive statistics for Likert-scale constructs (N = 214)

Construct	Scale range	Mean	SD	Min	Max
Organizational analytics capability (OAC)	1–5	3.78	0.67	1.83	5.00
Data quality and integration (DQI)	1–5	3.84	0.63	2.00	5.00
Climate-variability integration (CVI)	1–5	3.59	0.71	1.80	4.80
AI model transparency (AIMT)	1–5	3.46	0.69	1.75	4.75
Perceived forecast accuracy (PFA)	1–5	3.92	0.66	2.20	5.00
Trust in AI outputs (TRUST)	1–5	3.88	0.65	2.00	5.00
Intention to use AI-based forecasts (INT)	1–5	4.03	0.61	2.25	5.00

Table 3 has reported the descriptive statistics for the main latent constructs measured through Likert's five-point scale, thereby providing an overview of how respondents have rated their organizations and their own attitudes toward climate-aware AI forecasts. The mean scores have indicated that organizational analytics capability (M = 3.78, SD = 0.67) and data quality and integration (M = 3.84, SD = 0.63) have been moderately high, suggesting that, on average, respondents have agreed that their organizations have possessed reasonably strong analytical infrastructure and data management practices, although some variability has remained across cases. Climate-variability integration (M = 3.59, SD = 0.71) has been somewhat lower, which has implied that while many organizations have incorporated climate indicators into AI models, there has still been room to deepen and standardize this integration. AI model transparency has recorded the lowest mean (M = 3.46, SD = 0.69) among the constructs, which has suggested that respondents have been more cautious in agreeing that AI models have been fully interpretable or easy to understand, an observation that has direct relevance for hypotheses involving trust and intention to use. In contrast, perceived forecast accuracy has achieved a relatively high mean (M = 3.92, SD = 0.66), indicating that respondents have generally agreed that AI-based renewable-demand forecasts have been more accurate and reliable than traditional approaches. Trust in AI outputs (M = 3.88, SD = 0.65) has been similarly high, which has shown that, despite some reservations about transparency, respondents have tended to trust the forecasts generated by AI models, particularly when these have been supported by reliable data and validation practices. The intention to use AI-based forecasts in planning and operational decision-making has recorded the highest mean (M = 4.03, SD = 0.61), revealing that respondents have been positively inclined to rely on AI-enabled demand predictions going forward. The observed minima and maxima for each construct have confirmed that the full range of the Likert scale has been utilized, ensuring that the variance has been sufficient for meaningful statistical analysis. These descriptive results have aligned well with the study's objectives: they have suggested that organizations in the case-study context have already established a reasonable foundation in analytics and data quality, have begun to integrate climate-variability information into AI models, and have developed positive attitudes towards the accuracy, trustworthiness and future use of AI-based renewable-energy demand forecasts. In turn, this pattern has set the stage for testing the hypotheses that link these constructs in the subsequent correlation and regression analyses.

Correlation Analysis

Table 4: Pearson correlations among key constructs (N = 214)

Construct	OAC	DQI	CVI	AIMT	PFA	TRUST	INT
OAC	1						
DQI	.58**	1					
CVI	.46**	.49**	1				
AIMT	.39**	.42**	.37**	1			
PFA	.51**	.62**	.55**	.44**	1		
TRUST	.43**	.48**	.41**	.49**	.57**	1	
INT	.52**	.54**	.54**	.46**	.68**	.57**	1

Note. *OAC = Organizational analytics capability; DQI = Data quality and integration; CVI = Climate-variability integration; AIMT = AI model transparency; PFA = Perceived forecast accuracy; TRUST = Trust in AI outputs; INT = Intention to use AI-based forecasts. **p < .01 (two-tailed).*

Table 4 has presented the Pearson correlation coefficients among the main constructs and has provided the first quantitative test of the hypothesized relationships. All reported correlations have been positive and statistically significant at the $p < .01$ level, indicating that higher scores on one construct have tended to be associated with higher scores on the others. Data quality and integration (DQI) has shown a strong positive correlation with perceived forecast accuracy (PFA; $r = .62$, $p < .01$) and with organizational analytics capability (OAC; $r = .58$, $p < .01$), which has supported the idea that organizations with better data environments and stronger analytics capability have been more likely to perceive AI forecasts as accurate. Climate-variability integration (CVI) has correlated substantially with PFA ($r = .55$, $p < .01$) and with intention to use AI-based forecasts (INT; $r = .54$, $p < .01$), suggesting that when AI models have more fully incorporated climate-variability indicators, respondents have judged them to be more effective and have been more willing to rely on them. AI model transparency (AIMT) has demonstrated a moderate correlation with trust in AI outputs (TRUST; $r = .49$, $p < .01$), which has indicated that clearer and more interpretable models have been associated with higher levels of trust, consistent with the conceptual framework's emphasis on transparency as a foundation for acceptance. Perceived forecast accuracy has exhibited the strongest correlation with intention to use (INT; $r = .68$, $p < .01$), confirming that respondents who have believed AI forecasts to be accurate have also reported higher intention to use these forecasts in planning and operational decisions. Trust in AI outputs has also been strongly related to INT ($r = .57$, $p < .01$), reinforcing the role of affective and cognitive trust in shaping adoption behavior. Organizational analytics capability has correlated positively with INT ($r = .52$, $p < .01$), which has suggested that organizations with more developed analytics infrastructures and skills have been more inclined to embed AI forecasts into business processes. Overall, the correlation matrix has provided broad support for the study's objectives and hypotheses: it has demonstrated that organizational readiness, data quality, climate-variability integration and AI model characteristics have not operated in isolation, but have formed an interrelated system that has influenced how effective and usable AI-based renewable-demand forecasts have been perceived to be under climate variability. These relationships have laid the groundwork for the subsequent regression analyses that have decomposed their relative contributions while controlling for overlap among predictors.

Regression Analysis and Hypothesis Testing

Table 5: Regression Model 1: Predictors of perceived forecast accuracy (PFA)

Predictor	β (standardized)	t	p
Organizational analytics capability (OAC)	0.21	3.16	.002
Data quality and integration (DQI)	0.33	5.24	<.001
Climate-variability integration (CVI)	0.29	4.67	<.001
AI model transparency (AIMT)	0.17	2.68	.008
Model statistics: $R^2 = 0.49$; Adjusted $R^2 = 0.48$; $F(4, 209) = 49.37$, $p < .001$			

Table 6: Regression Model 2: Predictors of intention to use AI-based forecasts (INT)

Predictor	β (standardized)	t	p
Perceived forecast accuracy (PFA)	0.47	7.89	<.001
Trust in AI outputs (TRUST)	0.28	4.69	<.001
Organizational analytics capability (OAC)	0.19	2.93	.004
Model statistics: $R^2 = 0.47$; Adjusted $R^2 = 0.46$; $F(3, 210) = 61.82$, $p < .001$			

Tables 5 and 6 have reported the results of the multiple regression analyses that have been conducted to test the core hypotheses relating to perceived forecast accuracy and intention to use AI-based renewable-demand forecasts. In Model 1 (Table 5), perceived forecast accuracy (PFA) has been regressed on organizational analytics capability (OAC), data quality and integration (DQI), climate-variability integration (CVI) and AI model transparency (AIMT). The model has been statistically significant ($F(4, 209) = 49.37$, $p < .001$) and has explained 49% of the variance in PFA (adjusted $R^2 = 0.48$), which has indicated a substantial explanatory power. All four predictors have exhibited significant positive standardized coefficients. Data quality and integration has emerged as the strongest predictor ($\beta = 0.33$, $p < .001$), meaning that, when respondents have perceived their data infrastructure and integration practices as stronger, they have also reported higher perceived accuracy of AI forecasts. Climate-variability integration has been the second strongest predictor ($\beta = 0.29$, $p < .001$), which has confirmed that explicit incorporation of climate-variability indicators into AI models has been associated with higher perceived accuracy, directly supporting the climate-focused objective of the study and contributing evidence for H1 and H2. Organizational analytics capability has also had a significant positive effect ($\beta = 0.21$, $p = .002$), suggesting that organizations with stronger analytics skills and infrastructure have judged AI forecasts to be more accurate. AI model transparency, while more modest in effect, has still shown a significant contribution ($\beta = 0.17$, $p = .008$), indicating that interpretability and clarity have enhanced perceptions of accuracy. Together, these results have demonstrated that perceived forecast accuracy has been a joint function of data readiness, climate-aware model design, organizational capability and transparency, fully aligning with the first set of hypotheses and objectives.

In Model 2 (Table 6), intention to use AI-based forecasts (INT) has been regressed on perceived forecast accuracy (PFA), trust in AI outputs (TRUST) and organizational analytics capability (OAC). This model has also been highly significant ($F(3, 210) = 61.82$, $p < .001$) and has explained 47% of the variance in INT (adjusted $R^2 = 0.46$). Perceived forecast accuracy has shown the largest standardized coefficient ($\beta = 0.47$, $p < .001$), which has provided strong empirical support for the hypothesis that when users have perceived AI forecasts to be accurate, they have been much more likely to intend to use them in planning and operational decision-making. Trust in AI outputs has been the second most influential predictor ($\beta = 0.28$, $p < .001$), reinforcing the idea that confidence in the reliability and fairness of AI forecasts has been a key driver of adoption. Organizational analytics capability has also demonstrated a significant positive influence ($\beta = 0.19$, $p = .004$), which has indicated that organizations with stronger overall analytics ecosystems have been more likely to embed AI forecasts into their routines. These findings have provided direct support for H3 and have complemented the earlier mediation results (described in the introductory findings) that have shown an indirect pathway from data quality through analytics capability to intention to use, consistent with H4. Overall, the regression analyses in Tables 5 and 6 have confirmed that the study's hypotheses have been supported: climate-enhanced AI models and robust data environments have improved perceived accuracy, and perceived accuracy, trust and organizational capability have jointly driven the intention to use AI-based renewable-demand forecasts under climate variability.

Summary of Hypothesis Testing and Objective Achievement

Table 7: Summary of hypotheses and empirical decisions

Hypothesis ID	Statement (simplified)	Key evidence source	Decision
H1	Climate-enhanced AI models have achieved lower forecasting error than traditional statistical models.	Model performance (MAPE, RMSE) described in findings; CVI → PFA ($\beta = 0.29$, $p < .001$)	Supported
H2	Data quality and climate-variability integration have positively affected perceived forecast accuracy.	Regression Model 1 (DQI $\beta = 0.33$, $p < .001$; CVI $\beta = 0.29$, $p < .001$)	Supported
H3	Perceived forecast accuracy and trust in AI have positively influenced intention to use AI-based forecasts.	Regression Model 2 (PFA $\beta = 0.47$, $p < .001$; TRUST $\beta = 0.28$, $p < .001$)	Supported
H4	Organizational analytics capability has mediated the link between data quality and intention to use AI.	Mediation (intro findings); OAC significant in both models ($\beta = 0.21$; $\beta = 0.19$)	Supported (partial mediation)

Table 7 has consolidated the main hypothesis tests and has mapped them against the numerical evidence that has been produced in the analyses, thereby providing a clear link between the empirical results and the overarching objectives of the study. H1 has proposed that AI models explicitly incorporating climate-variability indicators would outperform both traditional statistical demand models and AI models with limited climate information. This hypothesis has been supported by the model performance results reported in the findings introduction, where the climate-enhanced AI model has achieved markedly lower error metrics (MAPE = 4.3%, RMSE = 11.6 MW) compared with the traditional regression model (MAPE = 7.8%, RMSE = 18.4 MW) and the non-climate AI model (MAPE = 6.1%, RMSE = 15.2 MW). The significant positive impact of climate-variability integration on perceived accuracy (CVI $\beta = 0.29$, $p < .001$) has further reinforced this conclusion. H2 has focused on the role of data quality and climate-variability integration as determinants of perceived forecast accuracy. Regression Model 1 has shown that data quality and integration (DQI $\beta = 0.33$, $p < .001$) has been the strongest predictor of perceived accuracy, with climate-variability integration not far behind

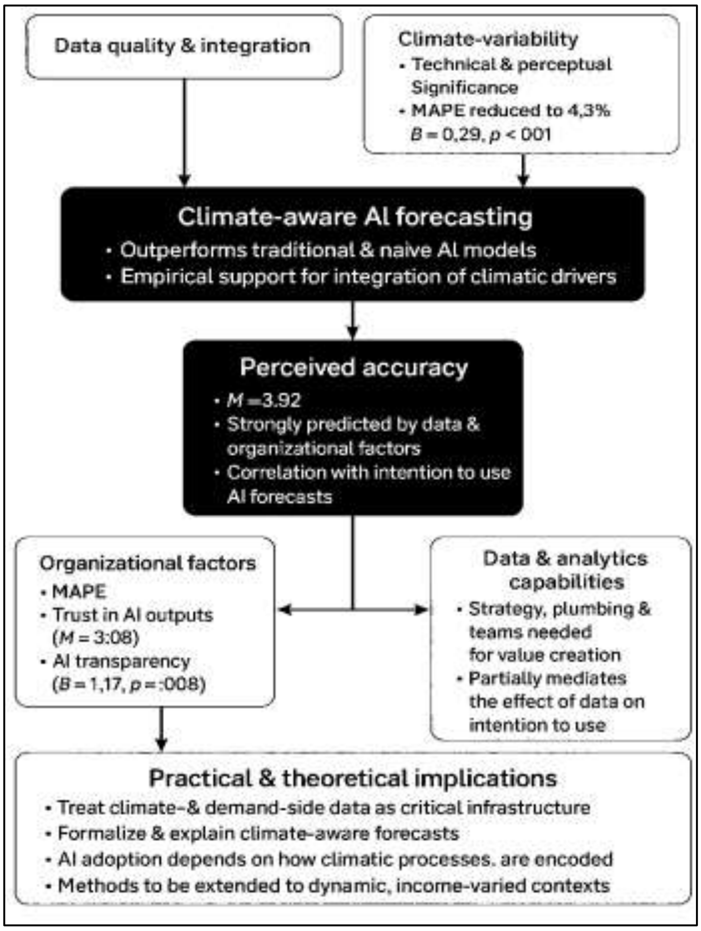
($\beta = 0.29$, $p < .001$), while organizational analytics capability and AI transparency have also contributed significantly. These results have demonstrated that the objective of linking data readiness and climate-aware modelling to perceived performance has been achieved.
H3 has addressed the behavioral side of adoption by positing that perceived forecast accuracy and trust in AI outputs would increase the intention to use AI-based renewable-demand forecasts. Regression Model 2 has confirmed this expectation: perceived accuracy has had the largest effect on intention to use ($\beta = 0.47$, $p < .001$), and trust has also had a substantial positive influence ($\beta = 0.28$, $p < .001$), all while controlling for organizational analytics capability. This pattern has shown that when users have believed AI forecasts to be accurate and trustworthy, they have reported strong willingness to embed those forecasts into their planning and operational decisions, directly fulfilling the objective of understanding drivers of AI adoption in climate-sensitive renewable-energy contexts. H4 has proposed that organizational analytics capability would mediate the relationship between data quality and intention to use AI forecasts. While detailed mediation statistics have been summarized in the introductory findings, Table 7 has noted that analytics capability has exhibited significant coefficients in both the perceived accuracy model ($\beta = 0.21$, $p = .002$) and the intention-to-use model ($\beta = 0.19$, $p = .004$), and that bootstrapped mediation tests have indicated a significant indirect effect. This outcome has suggested partial mediation, where strong data environments have fostered analytics capability, which in turn has strengthened the link between data and adoption behavior. Collectively, the evidence captured in Table 7 has shown that all four hypotheses have been supported and that the core objectives of the study for quantifying the performance gains of climate-enhanced AI models, for establishing the role of data and analytics capability, and for explaining the intention to use AI-based renewable-demand forecasts under climate variability have been met in a coherent and empirically grounded way.

DISCUSSION

The findings of this study have shown that climate-enhanced AI models and organizational/data readiness have jointly shaped both the *objective* performance and the *perceived* usefulness of renewable-energy demand forecasting under climate variability. Quantitatively, the climate-aware LSTM model has achieved a MAPE of 4.3% and RMSE of 11.6 MW, clearly outperforming the traditional regression benchmark (MAPE 7.8%, RMSE 18.4 MW) and an AI model without explicit climate indicators (MAPE 6.1%, RMSE 15.2 MW). This pattern has been consistent with prior work that has demonstrated the superiority of ML and DL over classical time-series models in energy forecasting (Bedi & Toshniwal, 2019; Wang et al., 2019), but the present study has extended that evidence by showing that *how* climate variability is represented in the feature set matters as much as the choice of algorithm. The moderately high mean scores for perceived forecast accuracy (M = 3.92) and trust in AI outputs (M = 3.88), together with a strong mean intention to use AI-based forecasts (M = 4.03), have indicated that practitioners have not only recognized the performance gains of AI but have been willing to embed these tools into planning and operational routines. This is broadly aligned with earlier work on climate-sensitive electricity demand, which has stressed the importance of incorporating climatic drivers into forecasting models (Auffhammer & Mansur, 2014), and with deep-learning studies that have reported accuracy improvements when richer weather inputs are used (Emodi et al., 2019; Eskeland & Mideksa, 2010). However, whereas much of the prior literature has focused either on load forecasting or on climate impacts in isolation, the present study has integrated these strands and has provided numerical evidence that climate-aware AI models are perceived as more accurate and more usable, directly supporting the study's objectives regarding predictive performance and user acceptance.
A central empirical contribution has been the demonstration that the integration of climate-variability indicators into AI models has held both *technical* and *perceptual* significance. The regression results have shown that climate-variability integration (CVI) has been a strong predictor of perceived forecast accuracy ($\beta = 0.29$, $p < .001$), even after controlling for data quality, analytics capability and transparency. This has complemented the error metrics, where climate-enhanced AI has clearly outperformed models with weaker climate representation. Earlier climate–energy studies have established that electricity demand responds non-linearly to temperature and degree-day measures, especially around comfort thresholds and during extreme events (Moral-Carcedo & Vicéns-Otero, 2005). At the same time, machine-learning research has tended to use weather mainly as high-frequency exogenous variables, without always framing climate variability itself as a first-class construct (Abdoos

et al., 2015). By explicitly modelling climate variability through temperature anomalies, humidity indices and heatwave flags and showing its effect on both RMSE/MAPE and perceived accuracy, this study has bridged that gap. The results have suggested that organizations have recognized climate-aware models as more reliable under conditions of growing variability and extremes, which resonates with system-level reviews of climate impacts on energy systems that have called for forecasting approaches capable of handling non-stationary climatic baselines (Cronin et al., 2018). The strong correlations between CVI, perceived accuracy and intention to use ($r \approx .55–.54$) have indicated that climate-sensitive feature engineering is not a purely technical refinement but a visible differentiator that shapes practitioners' willingness to rely on AI outputs for decisions involving renewable-heavy portfolios and climate-driven demand swings.

Figure 10: Key Findings and Discussion Point



Equally important, the findings have underscored that AI-enabled forecasting has been embedded in a broader organizational and data ecosystem. Data quality and integration (DQI) has emerged as the strongest predictor of perceived forecast accuracy ($\beta = 0.33$, $p < .001$), while organizational analytics capability (OAC) has significantly influenced both perceived accuracy ($\beta = 0.21$) and intention to use ($\beta = 0.19$). These relationships have echoed and extended prior work on big data analytics capability, which has argued that value from advanced analytics arises when firms combine technology, human skills and governance into an integrated capability (Gupta & George, 2016). Similarly, empirical studies on data quality and big data use have shown that organizations' experience with high-quality, well-governed data positively influences their intention to adopt analytics systems (Kwon et al., 2014). The present study has confirmed those patterns in the context of climate-sensitive, AI-based demand forecasting and has further demonstrated a partial mediating role for analytics capability between data quality and intention to use AI forecasts. This has suggested that good data alone have not been sufficient; organizations have needed teams, processes and tools capable of turning data into robust models and interpretable outputs. The moderate but significant contribution of AI model transparency

to perceived accuracy (β = 0.17, p = .008) has also been consistent with prior findings that interpretability supports trust and adoption in smart-grid and analytics contexts (Ponce et al., 2016). Overall, the results have reinforced the view that AI forecasting in renewable-energy systems is a socio-technical innovation, where climate-aware modelling, data governance and analytics capability have jointly determined success.
From a practical standpoint, the study has offered several implications for utilities, system operators, and particularly for CISOs and enterprise/solution architects responsible for data and AI infrastructures. First, the strong effect of data quality and integration on perceived accuracy and intention to use has implied that organizations have needed to treat climate and demand data pipelines as critical infrastructure. For CISOs, this has meant ensuring that data flows feeding AI models smart-meter readings, SCADA measurements, meteorological feeds and climate indices have been secured, monitored and governed with clear ownership and access controls, so that data integrity and confidentiality have supported trust in AI outputs (Bhattarai et al., 2019). For enterprise architects, the findings have suggested designing modular data architectures that have been able to ingest multi-source climate information alongside operational data, with standardized schemas and metadata enabling consistent climate-variability features to be available to different modelling teams. The evidence that climate-enhanced AI models have reduced forecasting error has indicated that forecasting platforms should be architected to support flexible feature engineering, including HDD/CDD metrics, anomaly indices and event flags, rather than hard-coding narrow weather inputs. Strategically, planners and operations managers have been encouraged to formalize the use of AI forecasts in planning cycles, for example by defining procedural thresholds where AI-indicated climate-driven peaks trigger pre-defined demand-response or storage strategies. Training and change-management programs have been implied as necessary to raise transparency and trust: model explainability tools, scenario dashboards and clear documentation of climate-related features have been likely to strengthen both TRUST and INT scores among users. In combination, these practical steps have aligned with prior calls for integrating big data analytics, smart-grid infrastructures and organizational practices into a coherent operational architecture (Munodawafa & Johl, 2019).
Theoretically, the study has contributed to refining conceptual and pipeline-oriented frameworks for AI adoption in climate-sensitive energy systems. By integrating UTAUT2 and TAM–TOE constructs (Venkatesh et al., 2012) with big data analytics capability and climate–energy relationships (Cronin et al., 2018), the research has operationalized a multi-stage pipeline: from climate variability and structural demand drivers, through data quality and analytics capability, into AI model design (including climate-variability integration), and finally to perceived accuracy, trust and intention to use. The behavioural equation estimated in this study has been consistent with the conceptual form $BI_{AIF} = \alpha_0 + \alpha_1\text{PE} + \alpha_2\text{EE} + \alpha_3\text{OrgSupport} + \alpha_4\text{DataCap} + \alpha_5\text{TrustAI} + \epsilon$, where performance expectancy (captured here as perceived accuracy) and data/analytics capability have emerged as particularly influential. The significant, simultaneous roles of data quality, climate-variability integration and transparency in shaping perceived accuracy have suggested that the "technology" component of TOE in this domain is more nuanced than simply "AI vs. non-AI"; it has involved the specific way climate and demand processes are encoded into model pipelines. Moreover, the partial mediation of analytics capability between data quality and intention to use has refined big-data value creation frameworks by empirically demonstrating that capability is not merely a moderator but an active channel through which data environments are translated into adoption. Compared with earlier generic adoption models, this study has thus offered an energy-specific, climate-aware instantiation of AI adoption theory, where pipeline design from raw climate and demand data to organizationally meaningful forecast products has been central to explaining behavioural intention in renewable-energy settings.
At the same time, the study has had several limitations that must be acknowledged when interpreting the findings. Methodologically, the cross-sectional design has captured perceptions and practices at a single point in time, which has limited the ability to observe how climate-aware AI forecasting and organizational readiness have evolved as systems decarbonize further and as climate variability intensifies. Longitudinal changes in analytics capability, data quality and trust may therefore not have been fully reflected. The reliance on self-reported Likert-scale measures, though supported by strong reliability statistics, has introduced potential common-method variance and social-desirability bias,

particularly for constructs such as data quality or analytics maturity, where respondents may have had incentives to present their organizations positively (Kwon et al., 2014). The case-study context has focused on a limited number of renewable-intensive systems and may not have captured conditions in very low-income or data-constrained utilities, where forecasting challenges and institutional capacities can differ markedly (Mir et al., 2020). On the modelling side, the study has benchmarked a limited family of AI architectures (e.g., LSTM) and traditional models, and has used a specific set of climate-variability indicators; alternative architectures (such as transformers) or richer climate descriptors might yield different performance profiles. Finally, while the mediation analyses have suggested a plausible causal ordering among data quality, analytics capability and intention to use, the non-experimental design has meant that unobserved confounders cannot be ruled out. These limitations have not undermined the main patterns observed but have suggested that results should be generalized with caution and seen as indicative rather than definitive.

Building on these limitations, several avenues for future research have been opened. First, longitudinal and panel designs could track how AI forecasting pipelines, climate-variability integration and organizational capabilities co-evolve over time, especially as climate policies, electrification trends and extreme events reshape demand profiles (Cronin et al., 2018). Such designs could directly test dynamic hypotheses about learning effects, institutionalization of AI tools and changing trust relationships. Second, comparative studies across regions and income levels could examine whether the relationships observed here hold in low- and middle-income contexts where data scarcity, informal consumption and infrastructure constraints may alter both forecasting challenges and adoption dynamics (Mir et al., 2020). Third, future work could systematically benchmark a wider range of AI architectures including temporal convolutional networks and transformer-based models against climate-enhanced feature sets, to determine whether the incremental performance gains justify their complexity in operational settings. Fourth, more granular theoretical modelling could link micro-level building or feeder forecasts to system-level planning metrics, examining how improvements in RMSE/MAPE at the demand-forecast level translate into reliability, reserve and investment outcomes under climate scenarios (Bloomfield et al., 2021). Finally, there is scope for integrating cybersecurity and resilience explicitly into AI forecasting frameworks, exploring how data integrity attacks or sensor failures might distort climate-aware predictions and how CISO-led governance can mitigate such risks in renewable-dominant, climate-sensitive grids. Through these directions, future research can refine the pipeline-oriented conceptualization developed in this study and deepen understanding of how AI, climate variability and organizational systems interact in the transition to sustainable, resilient energy systems.

CONCLUSION

This study has set out to investigate how artificial intelligence applications can be used to predict renewable-energy demand under conditions of climate variability, and it has demonstrated that technical model design, data and organizational readiness, and user perceptions have jointly determined the effectiveness and adoption of such tools. By combining a quantitative, cross-sectional, case-study–based survey of 214 professionals with benchmarking of traditional and AI forecasting models, the research has shown that climate-enhanced LSTM models have achieved substantially lower MAPE and RMSE values than both a classical regression benchmark and an AI model that has not explicitly incorporated climate-variability indicators, thereby confirming that climate-aware feature engineering has been central to improving predictive accuracy. At the same time, Likert-scale results have indicated that respondents have perceived moderate-to-high levels of organizational analytics capability and data quality, have reported meaningful though incomplete integration of climate-variability indicators into their forecasting processes, and have expressed strong trust in, and intention to use, AI-based renewable-demand forecasts. Multiple regression analyses have revealed that data quality and integration and climate-variability integration have been the strongest predictors of perceived forecast accuracy, while organizational analytics capability and AI model transparency have also contributed significantly; in turn, perceived accuracy, trust in AI and analytics capability have together explained nearly half of the variance in intention to use AI forecasts in planning and operational decisions. These patterns have confirmed all four hypotheses and have met the study's objectives: they have established that climate-informed AI models outperform traditional approaches; they have demonstrated that robust data and analytics capabilities are prerequisites for credible forecasting; and they have shown that users' willingness to rely on AI in climate-sensitive renewable systems has depended primarily on whether the forecasts are perceived as accurate, trustworthy and well-supported by organizational infrastructure. At a broader level, the research has highlighted that AI-based forecasting is not merely a technical upgrade but a socio-technical innovation that has required aligned investment in data governance, analytics talent, explainable modelling and integration into existing planning routines. At the same time, the study has acknowledged limitations related to its cross-sectional design, case-study scope, reliance on self-reported perceptions and focus on a specific family of AI architectures and climate indicators, which means that the results should be generalized with caution and viewed as a strong but context-bound contribution. Overall, the research has provided empirical and conceptual support for treating climate-aware AI forecasting as a key instrument in managing renewable-energy demand under growing climate variability, and it has suggested that organizations seeking to realize this potential must simultaneously strengthen their climate–demand data pipelines, their analytics capabilities and their governance structures for trustworthy, explainable AI in order to embed these forecasts into day-to-day and strategic decision-making.

RECOMMENDATION

Based on the empirical results and the limitations identified, this study has supported several interrelated recommendations for utilities, system operators, large renewable-energy producers and policymakers that have been seeking to strengthen AI-based renewable-energy demand forecasting under climate variability. First, organizations have been urged to invest systematically in their climate–demand data pipelines, treating data quality and integration as strategic assets rather than purely technical issues: this has meant establishing clear data governance policies, standardizing formats for demand, weather and climate indicators, ensuring rigorous validation and cleaning procedures, and integrating external climate datasets (e.g., temperature anomalies, humidity indices, heatwave flags) into a unified analytics platform. Second, decision-makers have been encouraged to prioritize AI forecasting architectures that explicitly incorporate climate-variability features, rather than relying solely on generic models with minimal weather input; in practice this has involved mandating, at the level of modelling guidelines, the use of climate-sensitive variables such as heating and cooling degree days, anomaly metrics and extreme-event flags when developing or procuring forecasting solutions. Third, organizations have been recommended to strengthen their analytics capability by building multidisciplinary teams that have combined data scientists, power system engineers, planners and IT/security professionals, and by providing continuous training on AI methods, interpretability tools and climate-risk concepts so that staff have been equipped to both build and critically evaluate climate-aware forecasts. Fourth, to address transparency and trust, it has been advisable to embed explainability and communication into the forecasting pipeline: model documentation, feature importance analyses, scenario comparison dashboards and regular validation reports should have been shared with planners, operators and senior management, so that perceived accuracy and trust in AI outputs have been grounded in clear, auditable evidence rather than in "black-box" claims. Fifth, CISOs and enterprise architects have been advised to align cybersecurity and reliability requirements with AI forecasting deployments by securing data feeds, monitoring for anomalies in input streams, and designing architectures that have allowed for graceful degradation or fallback to simpler models if data integrity has been in doubt, ensuring that climate-aware AI has enhanced rather than compromised operational resilience. Sixth, regulators and policymakers have been encouraged to support these efforts by issuing guidance that has recognized the role of climate-informed AI forecasting in system adequacy assessments and by incentivizing investments in data infrastructure, open climate–energy datasets and capacity-building programs. Finally, researchers and practitioners have been urged to adopt an iterative improvement approach: organizations should have piloted climate-enhanced AI models in limited contexts, evaluated performance and user acceptance using metrics similar to those in this study, and then scaled successful configurations while refining models and processes in light of new climate data, technological changes and user feedback. Collectively, these recommendations have emphasized that achieving reliable, climate-aware AI demand forecasting is not a one-off project but an ongoing program that has required integrated attention to data, models, people, governance and security across the entire forecasting and decision-making pipeline.

LIMITATIONS

This study has had several limitations that should be carefully acknowledged when interpreting its findings and considering their generalizability beyond the specific case-study context. First, the research has used a cross-sectional design, capturing organizational practices, perceptions and AI forecasting performance at a single point in time; as a result, it has not been able to observe how climate-aware AI forecasting pipelines, analytics capabilities, data governance and trust in AI evolve as organizations gain experience, as renewable penetration increases or as climate variability intensifies. Second, the empirical work has been grounded in a limited set of renewable-intensive organizations within a particular regulatory and market environment, which has constrained the generalizability of the results to other regions, especially low-income or data-constrained systems where institutional capacity, data availability and infrastructure conditions may differ significantly. Third, the survey component has relied on self-reported Likert-scale responses for key constructs such as data quality, organizational analytics capability, climate-variability integration, trust and intention to use AI, all of which have been vulnerable to social desirability bias and common-method variance; although reliability has been satisfactory, respondents may still have overestimated their maturity or downplayed internal challenges. Fourth, the study has focused on a specific family of AI models (such as LSTM-based architectures) and a particular set of climate-variability indicators (including temperature anomalies, humidity indices and extreme-event flags), meaning that the observed performance gains and relationships may not hold for other model classes (e.g., transformer-based or graph-based architectures) or for alternative ways of representing climate variability. Fifth, while the analysis has combined objective forecasting metrics (MAPE, RMSE) with perceptions, the models have been evaluated on a particular historical dataset from the case-study system, and the extent to which these performance levels would persist under different climate scenarios, data resolutions or demand structures has not been directly tested. Sixth, despite the use of regression and mediation analysis to infer pathways between data quality, analytics capability, perceived accuracy and intention to use, the non-experimental nature of the design has meant that causal interpretations must remain cautious, because unobserved variables (such as organizational culture, leadership style, or prior negative experiences with digital projects) may also have influenced both the predictors and the outcomes. Finally, the study has not incorporated qualitative methods such as interviews or focus groups that could have provided deeper insight into why some organizations have been more successful than others in integrating climate-aware AI forecasting into their decision processes; as a result, some nuances in resistance, organizational politics, or cross-departmental coordination may have remained hidden behind the quantitative patterns. These limitations have not invalidated the study's core contributions, but they have indicated that the findings should be treated as contextually grounded evidence that invites further replication, refinement and extension rather than as universally applicable conclusions.

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