

Designing a Flexibility Management Model Using Artificial Intelligence in Active Distribution Networks with Consumer and Producer Participation

Mahmoud. Fereydouni¹ 

¹ Department of Electrical Engineering, Technical and Vocational University (TVU), Tehran, Iran

* Corresponding author email address: mfereydouni@tvu.ac.ir

Article Info

Article type:

Original Research

How to cite this article:

Fereydouni, M., (2027). Designing a Flexibility Management Model Using Artificial Intelligence in Active Distribution Networks with Consumer and Producer Participation. *Journal of Resource Management and Decision Engineering*, 6(6), 1-18.
<https://doi.org/10.61838/kman.jrmde.445>



© 2027 the authors. Published by KMAN Publication Inc. (KMANPUB). This is an open access article under the terms of the Creative Commons Attribution-NonCommercial 4.0 International (CC BY-NC 4.0) License.

ABSTRACT

This study aimed to design and validate an artificial intelligence-based flexibility management model for active distribution networks with the participation of consumers and producers. This applied developmental study employed an exploratory sequential mixed-method design. In the qualitative phase, 18 experts in electricity distribution, smart grids, distributed generation, energy management, and artificial intelligence were purposively selected in Tehran and interviewed using a semi-structured protocol until theoretical saturation was achieved. The qualitative findings were used to develop a 52-item questionnaire covering 11 model constructs. In the quantitative phase, 300 managers, engineers, technical specialists, and energy-sector experts completed the questionnaire. Data were analyzed using SPSS 29 and SmartPLS 4. Measurement-model evaluation included indicator loadings, Cronbach's alpha, composite reliability, average variance extracted, heterotrait-monotrait ratios, and variance inflation factors. The structural model was assessed using partial least squares structural equation modeling with 5,000 bootstrap resamples, path coefficients, R^2 , Q^2 , f^2 , SRMR, and NFI. Intelligent data and communication infrastructure significantly predicted artificial intelligence capabilities ($\beta = 0.624$, $p < 0.001$) and intelligent decision-making ($\beta = 0.214$, $p < 0.001$). Artificial intelligence capabilities significantly predicted forecasting and uncertainty management ($\beta = 0.671$, $p < 0.001$) and intelligent decision-making ($\beta = 0.486$, $p < 0.001$). Incentive and market mechanisms significantly influenced consumer and prosumer participation ($\beta = 0.537$, $p < 0.001$), which significantly predicted flexible demand management ($\beta = 0.458$, $p < 0.001$). Forecasting and uncertainty management ($\beta = 0.219$), flexible demand management ($\beta = 0.187$), distributed-generation coordination ($\beta = 0.231$), energy-storage management ($\beta = 0.143$), and intelligent decision-making ($\beta = 0.302$) all significantly predicted network operational flexibility (all $p < 0.01$). Network operational flexibility strongly predicted system-level flexibility outcomes ($\beta = 0.713$, $p < 0.001$). The model explained 68.4% of the variance in network operational flexibility and 50.8% of the variance in system-level flexibility outcomes. The findings indicate that effective flexibility management in active distribution networks requires the integrated development of intelligent infrastructure, AI capabilities, forecasting, distributed-resource coordination, demand-side flexibility, market incentives, and consumer and producer participation.

Keywords: Artificial Intelligence; Flexibility Management; Active Distribution Networks; Consumer Participation; Prosumers; Distributed Generation

1. Introduction

Electricity distribution networks are undergoing a fundamental transition from traditionally passive infrastructures toward active, intelligent, decentralized, and increasingly interactive systems. This transformation is driven by the rapid penetration of distributed energy resources, renewable generation, energy storage systems, electric vehicles, smart meters, digital communication technologies, and demand-side resources. In conventional distribution systems, electricity flows predominantly in one direction from centralized generation facilities to end users, and consumers generally play a passive role in electricity consumption. In contrast, active distribution networks are characterized by multidirectional energy flows, distributed generation, real-time information exchange, and the participation of consumers who can simultaneously act as producers, storage operators, and flexibility providers. These changes create major opportunities for improving efficiency, resilience, sustainability, and asset utilization, but they also introduce substantial uncertainty, operational complexity, variability, and coordination challenges. Electricity distribution companies must therefore move beyond conventional operating paradigms and develop more adaptive management structures capable of continuously balancing demand, distributed generation, network constraints, storage resources, and customer behavior. Previous research in Iranian electricity distribution companies has already demonstrated that organizational performance is highly dependent on environmental conditions, managerial systems, operational efficiency, and institutional capabilities, emphasizing that distribution-company performance cannot be understood exclusively through technical indicators (Bahrini et al., 2015; Pourabadolahankooch et al., 2021).

One of the most important concepts emerging from this transition is flexibility. In electricity systems, flexibility refers to the ability of resources and network operators to modify generation, consumption, storage, or power-flow patterns in response to variations in system conditions, market signals, operational constraints, and unforeseen disturbances. Flexibility has become especially important as intermittent renewable energy sources increase the mismatch between electricity production and demand across different periods. Conventional approaches relying mainly on network reinforcement and centralized generation are increasingly insufficient or economically inefficient for dealing with these variations. Active distribution networks

require a broader portfolio of flexible resources, including controllable distributed generation, responsive loads, battery storage, electric vehicles, and prosumer-owned resources. Flexibility management therefore involves identifying available flexible capacity, forecasting when and where flexibility will be required, activating appropriate resources, coordinating multiple participants, and evaluating the operational consequences of different decisions. Such management should not be restricted to short-term balancing; rather, it should be integrated with asset management, resilience planning, congestion mitigation, voltage control, outage management, and long-term distribution-network development. The importance of resilience has previously been emphasized in studies of electricity distribution companies, particularly in relation to the ability of distribution infrastructures to withstand severe environmental disturbances and recover from disruptions (Karami & Separi, 2016). Similarly, organizational risk-management approaches in electricity distribution companies have highlighted the need to systematically identify, evaluate, and manage operational and strategic risks rather than respond reactively after failures occur (Valizadeh & Hosseini, 2010).

The need for flexibility management is intensified by the increasing uncertainty of both supply and demand. Renewable resources such as solar and wind generation are inherently variable, while electricity consumption is influenced by weather, time of day, economic activity, consumer preferences, technology adoption, and behavioral responses to prices and incentives. Consequently, accurate understanding and prediction of consumption patterns have become essential for the reliable operation of active distribution networks. Zhang et al. demonstrated that dynamic electricity-consumption behaviors can be meaningfully grouped using advanced clustering techniques, illustrating the value of data-driven methods for recognizing heterogeneous patterns of electricity use (Zhang et al., 2021). Such findings have direct implications for flexibility management because consumers with different temporal consumption profiles are unlikely to provide identical forms or quantities of demand-side flexibility. A household with controllable electric heating, for example, may provide flexibility differently from a commercial consumer with shiftable industrial loads or a prosumer equipped with rooftop photovoltaic generation and battery storage. Therefore, the transition toward active distribution networks requires a move from aggregate demand assumptions toward

granular, dynamic, and behavior-sensitive models of consumption and production.

Artificial intelligence offers an important technological foundation for addressing this complexity. AI encompasses a broad range of computational approaches, including machine learning, deep learning, predictive analytics, intelligent optimization, pattern recognition, reinforcement learning, and adaptive decision-support systems. These approaches enable large volumes of heterogeneous and continuously changing data to be transformed into operational knowledge. In active distribution networks, AI can potentially be used to forecast load and renewable generation, detect anomalies, classify consumption behavior, estimate flexibility potential, optimize resource scheduling, coordinate distributed energy resources, identify congestion, support preventive maintenance, and facilitate real-time operational decisions. Unlike static rule-based approaches, AI-based systems can learn from historical and real-time data and update their predictions or control strategies when system conditions change. This capability is particularly relevant in networks characterized by uncertainty and nonlinear interactions among demand, distributed generation, storage, prices, and consumer behavior. The increasing relevance of AI across consumer-oriented environments has already been demonstrated in other sectors, where AI-based technologies influence decision-making, engagement, perceived value, and behavioral responses (Ho & Chow, 2023; Manikandan & Bhuvaneswari, 2024).

The importance of AI is not limited to computational efficiency. It can also alter the relationship between service providers and consumers. Research on AI-enabled consumer environments indicates that artificial intelligence can shape customer preferences, purchase decisions, engagement patterns, and perceived value by providing personalized recommendations, adaptive interactions, and data-driven services (Aggarwal et al., 2024; Amin, 2025). Rather has similarly shown that engagement with AI-based technologies is associated with users' perceptions of value and congruence between technological services and their individual expectations (Rather, 2025). Although these studies originate from domains outside electricity distribution, they are conceptually relevant to active distribution systems because flexibility management increasingly depends on voluntary consumer participation, digital interaction, personalized incentives, and responsiveness to automated recommendations or control signals. The effectiveness of AI-based flexibility programs

is therefore likely to depend not only on algorithmic accuracy but also on whether consumers perceive such systems as valuable, trustworthy, understandable, and compatible with their preferences.

The role of consumers has become particularly important as electricity users increasingly evolve into prosumers. Prosumers may consume electricity, generate power through rooftop photovoltaic systems or other distributed technologies, store energy, and participate in demand-response or local energy markets. Their resources can provide valuable flexibility by shifting consumption, reducing demand during critical periods, injecting locally generated electricity, or releasing stored energy when network constraints arise. However, technical availability does not automatically translate into effective participation. Abdelmotteleb et al. emphasized the importance of customer engagement in the provision of distribution-level flexibility products and showed that participation depends on how flexibility mechanisms are designed and how customers interact with them (Abdelmotteleb et al., 2022). Consumer engagement must therefore be treated as a central component of flexibility management rather than as a peripheral behavioral consideration. Without appropriate incentives, communication mechanisms, contractual structures, and understandable participation processes, potentially flexible resources may remain unavailable to distribution-system operators.

Changes in consumer behavior observed in broader digital environments further reinforce this point. Studies of technology adoption and post-pandemic consumer behavior have shown that individuals adapt their behavioral patterns when technological infrastructures, perceived convenience, expectations, and social environments change (Gupta & Mukherjee, 2022; Jayasingh et al., 2022). These observations are relevant to electricity systems because the introduction of smart meters, home energy-management systems, mobile energy applications, automated demand response, dynamic tariffs, and AI-based recommendations similarly changes the context within which energy decisions are made. Consumers who previously received electricity as a passive service are increasingly expected to respond to real-time information, incentives, or automated control mechanisms. Therefore, flexibility management in active distribution networks must account for technology adoption, behavioral heterogeneity, consumer willingness, and the usability of digital participation channels. AI may support this transition by segmenting users, predicting

responsiveness, personalizing incentives, and optimizing the timing of flexibility requests.

At the same time, the growing use of AI also introduces social, organizational, and workforce-related implications. AI-based automation may reshape professional roles, modify decision-making authority, and create new competency requirements for distribution-company employees. Fan emphasized that AI-driven automation creates both challenges and opportunities in labor markets and requires workforce adaptation and rehabilitation (Fan, 2024). In electricity distribution companies, this implies that successful adoption of AI-based flexibility management requires more than investment in algorithms and hardware. Employees must possess adequate digital literacy, analytical capabilities, operational knowledge, and confidence in AI-supported decision systems. Strategic human-resource management therefore becomes an enabling condition for technological transformation. Research within Iranian electricity distribution companies has highlighted the importance of strategic human-resource factors for organizational efficiency and sustainable performance (Samavi, 2021). Likewise, organizational culture can significantly affect employee behavior and safety-related performance in electricity distribution organizations, demonstrating that institutional values and internal management practices influence how technical systems are actually implemented and used (Rezaei Dizgah et al., 2022).

The organizational dimension is especially important because active distribution networks require close integration among technical departments, information-technology units, planning divisions, regulatory actors, consumers, distributed generators, and external technology providers. Such integration depends on knowledge exchange, organizational learning, and collaboration between industry and scientific institutions. Moghaddas Nodeh's examination of university-industry collaboration in the Tehran Province Electricity Distribution Company identified practical challenges affecting knowledge transfer and cooperative innovation (Moghaddas Nodeh, 2019). These challenges are highly relevant to AI adoption because sophisticated flexibility-management systems typically require interdisciplinary expertise in power engineering, data science, machine learning, communications, market design, and behavioral analysis. Distribution companies that operate in institutional silos may therefore experience difficulty translating technological advances into operational capabilities. Effective AI-enabled flexibility management requires governance arrangements that facilitate cooperation

among internal departments and external research, technology, and regulatory actors.

Another important issue concerns performance management and evaluation. Traditional electricity-distribution performance frameworks often emphasize indicators such as losses, outage duration, reliability indices, cost efficiency, and technical productivity. However, the emergence of active networks requires broader measures capable of capturing digital maturity, customer participation, renewable integration, operational adaptability, and flexibility utilization. Robust efficiency-evaluation methods have already been applied to electricity distribution companies to assess relative organizational performance under complex and uncertain conditions (Fallahi et al., 2019). Nevertheless, flexibility management requires performance assessment to extend beyond static efficiency. A technically efficient distribution company may still lack the digital capabilities necessary to forecast distributed resources, engage consumers, coordinate storage, or react adaptively to rapidly changing network conditions. Consequently, flexibility should increasingly be considered an organizational and system-level performance dimension in its own right.

Environmental sustainability further strengthens the case for flexible and intelligent electricity networks. As distribution companies accommodate increasing amounts of renewable and distributed generation, flexibility becomes essential for avoiding curtailment, reducing network congestion, and maximizing the value of clean-energy resources. Sustainability-oriented management research has shown the importance of combining environmental objectives with economic, operational, and organizational performance measures rather than evaluating sustainability through a single dimension (Fernández-González et al., 2023). Similar thinking can be applied to active electricity distribution networks, where flexibility decisions influence environmental performance, network investment, consumer welfare, system reliability, and operational costs simultaneously. Green organizational practices may also contribute to this transition. Yahya Pour et al. emphasized the relevance of green human-resource management within electricity distribution companies in northern Iran, suggesting that environmental objectives should become embedded in organizational practices and workforce management (Yahya Pour et al., 2022). AI-supported flexibility management can potentially reinforce such sustainability strategies by enabling more efficient use of

renewable resources and reducing reliance on carbon-intensive balancing solutions.

Despite these opportunities, active distribution-network flexibility is constrained by several technical and managerial challenges. Data may be incomplete, delayed, fragmented, or incompatible across systems. Communication infrastructures may not provide sufficient real-time visibility. Cybersecurity and privacy concerns may limit data sharing. Forecasting errors can lead to inappropriate flexibility activation, while poorly designed incentive mechanisms may produce weak consumer participation. Furthermore, distributed energy resources are heterogeneous in terms of ownership, controllability, response time, duration, and location. Their flexibility value is therefore context-dependent. A kilowatt of flexibility available at one feeder or time may not be equivalent to the same quantity elsewhere. AI-based systems must consequently incorporate spatial, temporal, technical, economic, and behavioral characteristics when identifying and dispatching flexibility resources. This requirement makes flexibility management a multidimensional optimization and governance problem rather than a simple demand-response exercise.

The Iranian electricity-distribution context makes these issues particularly important. Existing studies have highlighted challenges related to organizational performance, efficiency, resilience, human-resource management, safety culture, risk management, environmental management, and industry-university cooperation within Iranian distribution companies (Bahrini et al., 2015; Karami & Separi, 2016; Moghaddas Nodeh, 2019; Rezaei Dizgah et al., 2022; Samavi, 2021). Evidence concerning efficiency and scale also shows that distribution-company performance varies and that structural and managerial characteristics can affect operational outcomes (Pourabadolahankooch et al., 2021). These findings collectively suggest that the transition toward AI-enabled active distribution networks cannot be accomplished through isolated technological interventions. Rather, an integrated model is required in which digital infrastructure, artificial-intelligence capabilities, forecasting, distributed-generation coordination, energy storage, demand flexibility, consumer participation, organizational readiness, and market mechanisms are treated as interconnected components.

Furthermore, flexibility management should be designed around a reciprocal relationship between technological intelligence and human participation. AI can improve prediction and optimization, but consumers and producers

ultimately control many of the physical resources from which flexibility is obtained. Likewise, participants may be technically capable of responding but remain inactive if the economic and institutional environment does not provide sufficient motivation. Evidence from customer-engagement and technology-adoption studies indicates that perceived value, behavioral willingness, ease of participation, and technological acceptance strongly shape actual engagement (Abdelmotteleb et al., 2022; Ho & Chow, 2023; Jayasingh et al., 2022; Rather, 2025). AI-based systems should therefore not merely determine the technically optimal flexibility action; they should also incorporate likely consumer responses and enable differentiated strategies for diverse consumer and prosumer groups. Findings from studies examining AI and consumer behavior further indicate that intelligent systems can substantially influence user decisions and behavioral patterns, strengthening the rationale for integrating behavioral analytics into future flexibility platforms (Aggarwal et al., 2024; Amin, 2025; Manikandan & Bhuvaneshwari, 2024).

Accordingly, a comprehensive flexibility-management architecture should combine several interconnected layers. The first is a data and communication layer that enables real-time monitoring and information exchange. The second is an AI and analytics layer for forecasting, classification, anomaly detection, optimization, and adaptive learning. The third includes physical flexibility resources such as responsive loads, distributed generation, and storage systems. The fourth concerns consumer and producer participation, including incentives, market arrangements, and engagement mechanisms. The fifth is an operational decision layer through which available flexibility is activated in response to network requirements. Finally, an organizational and governance layer is necessary to ensure that technological decisions remain aligned with safety, resilience, sustainability, workforce capability, institutional objectives, and regulatory requirements. Integrating these layers can transform flexibility from an isolated technical service into a strategic management capability of the active distribution network.

Despite the growing body of research on electricity-distribution performance, resilience, efficiency, consumer engagement, AI-enabled behavior, and technology adoption, there remains a need for an integrated empirical model explaining how artificial intelligence, network infrastructure, consumer and producer participation, flexible resources, and intelligent decision-making interact to generate operational and system-level flexibility. Existing

studies frequently investigate these domains separately, while the emerging active-distribution environment requires their simultaneous consideration. Therefore, the aim of the present study was to design and validate an artificial intelligence-based flexibility management model for active distribution networks with the participation of consumers and producers.

2. Methods and Materials

The present study was an applied, developmental study conducted using an exploratory sequential mixed-method design to develop and validate a flexibility management model based on artificial intelligence for active distribution networks with the participation of consumers and distributed energy producers. The study was conducted in Tehran, Iran, during 2026 and consisted of two consecutive qualitative and quantitative phases. In the qualitative phase, the statistical population comprised university faculty members, senior managers, electrical distribution specialists, energy-system planners, smart-grid experts, artificial intelligence specialists, and professionals with practical or research experience in demand-side management, distributed generation, renewable energy resources, energy storage systems, active distribution networks, and electricity-market participation. Using purposive and criterion-based sampling, 18 experts were selected for semi-structured interviews. Eligibility criteria included holding at least a master's degree in electrical engineering, energy engineering, artificial intelligence, industrial engineering, or a closely related discipline; having at least 10 years of academic, managerial, or professional experience in the electricity or energy sector; and having demonstrable experience with smart distribution networks, distributed energy resources, demand response, artificial intelligence applications, or energy flexibility management. Interviews continued until theoretical saturation was achieved and no substantively new concepts emerged. Findings from the qualitative phase were used to identify the principal dimensions, components, and indicators of the proposed model and to construct the quantitative instrument. In the quantitative phase, the population consisted of managers, engineers, technical specialists, energy planners, and experts employed by electricity distribution organizations, energy-sector companies, consulting firms, technology companies, research centers, and organizations involved in smart-grid and distributed-energy projects in Tehran. A total of 312 participants were selected using stratified purposive

sampling to ensure representation of different technical and managerial areas. Of these, 300 participants provided complete and usable questionnaires, corresponding to a valid response rate of 96.15%. The sample size was considered adequate for structural equation modeling because it exceeded conventional minimum requirements based on the number of latent constructs, measurement indicators, and structural paths included in the conceptual model. Participation was voluntary, respondents were informed about the purpose of the research, confidentiality and anonymity were guaranteed, and the data were used exclusively for scientific purposes.

Data collection was conducted through a semi-structured expert interview protocol and a researcher-developed questionnaire constructed on the basis of the qualitative findings and the theoretical literature on active distribution networks, flexibility management, artificial intelligence, distributed energy resources, demand response, prosumer participation, and smart-grid operation. The semi-structured interview protocol contained open-ended questions designed to explore the determinants, mechanisms, infrastructure requirements, operational processes, and expected outcomes of AI-enabled flexibility management. The interviews focused particularly on the role of artificial intelligence in forecasting electricity demand and distributed generation, identifying available flexibility resources, optimizing network operation, coordinating flexible loads, integrating renewable generation and energy storage, managing uncertainty, supporting real-time decision-making, and enabling the participation of consumers and prosumers in flexibility provision. Participants were also asked about technological infrastructure, data quality and interoperability, regulatory requirements, economic incentives, consumer engagement, cybersecurity, organizational capabilities, and barriers to implementation. Each interview lasted approximately 45–70 minutes and was digitally recorded with the participant's permission and subsequently transcribed verbatim. The interview protocol was initially reviewed by three academic specialists in power systems and research methodology to establish clarity, relevance, and content coverage, and minor modifications were made before the formal interviews.

Based on the qualitative coding process, a preliminary pool of questionnaire items was generated to operationalize the components of the proposed flexibility management model. The initial instrument consisted of 58 items measuring the major dimensions identified during the qualitative phase, including intelligent data and

communication infrastructure, artificial-intelligence capabilities, forecasting and uncertainty management, flexible demand management, distributed-generation coordination, energy-storage management, consumer and prosumer participation, incentive and market mechanisms, network operational flexibility, intelligent decision-making, and system-level flexibility outcomes. All items were rated on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree), with higher scores representing a stronger presence or greater importance of the corresponding flexibility-management capability. Content validity was assessed by a panel of 12 experts in electrical power systems, smart grids, energy management, and artificial intelligence. The experts evaluated the necessity, relevance, clarity, and representativeness of each item. The content validity ratio and content validity index were calculated, and items failing to meet acceptable thresholds were revised or eliminated. Following expert assessment, 52 items were retained in the final questionnaire. Face validity was subsequently evaluated through a pilot administration to 20 specialists who were not included in the main quantitative sample, and wording changes were made where necessary to improve comprehensibility and reduce ambiguity. Construct validity was assessed in the main sample through confirmatory factor analysis and measurement-model evaluation. Internal consistency reliability was evaluated using Cronbach's alpha and composite reliability, with coefficients of 0.70 or higher regarded as acceptable. Convergent validity was examined through standardized factor loadings and average variance extracted, with factor loadings above 0.50 and average variance extracted values of at least 0.50 considered satisfactory. Discriminant validity was evaluated using the heterotrait-monotrait ratio, with values below 0.85 indicating adequate distinction among the latent constructs.

Qualitative and quantitative data were analyzed sequentially in accordance with the mixed-method design. In the qualitative phase, interview transcripts were analyzed using thematic analysis with an inductive-deductive coding procedure. After repeated reading of the transcripts, meaningful statements were identified and assigned initial codes. Similar codes were compared, merged, and organized into subcategories, followed by broader categories and overarching dimensions representing the architecture of AI-enabled flexibility management in active distribution networks. Constant comparison was applied throughout the coding process to refine conceptual boundaries and determine relationships among categories. Credibility of the

qualitative analysis was enhanced through member checking, peer review, and comparison of coding decisions between researchers. To examine coding consistency, a subset of interview transcripts was independently coded and inter-coder agreement was calculated. The qualitative analysis resulted in the conceptual framework subsequently operationalized in the quantitative phase.

Quantitative analyses were conducted using SPSS version 29 and SmartPLS version 4. Descriptive statistics, including frequency, percentage, mean, standard deviation, skewness, and kurtosis, were calculated to describe participant characteristics and the distribution of the research variables. Before testing the structural model, the quality of the measurement model was evaluated using indicator reliability, internal consistency reliability, convergent validity, discriminant validity, and multicollinearity diagnostics. Indicator loadings were expected to exceed 0.70, although loadings between 0.50 and 0.70 were retained when construct reliability and validity remained satisfactory. Cronbach's alpha and composite reliability values above 0.70, average variance extracted values above 0.50, heterotrait-monotrait ratios below 0.85, and variance inflation factor values below 5 were used as the principal acceptance criteria. Partial least squares structural equation modeling was then employed to test the hypothesized relationships among the dimensions of the flexibility management model. The significance of structural path coefficients was assessed using a bootstrapping procedure with 5,000 resamples, and relationships were regarded as statistically significant at $p < .05$. The explanatory power of the model was evaluated through the coefficient of determination (R^2), while predictive relevance was examined using Stone-Geisser's Q^2 criterion. Effect sizes (f^2) were calculated to determine the relative contribution of individual exogenous constructs to endogenous variables. Model fit was additionally evaluated using the standardized root mean square residual, with values below 0.08 interpreted as evidence of acceptable overall fit. Finally, the magnitude and statistical significance of the standardized path coefficients, together with the R^2 , Q^2 , f^2 , reliability, and validity indices, were used to validate the final model and determine how artificial intelligence capabilities, network infrastructure, flexible energy resources, consumer and producer participation, and market and organizational mechanisms jointly contribute to flexibility management in active electricity distribution networks.

3. Findings and Results

A total of 300 valid questionnaires were included in the quantitative analysis. Regarding the demographic and professional characteristics of the participants, 207 respondents (69.0%) were male and 93 (31.0%) were female. In terms of age, 36 participants (12.0%) were younger than 30 years, 96 (32.0%) were between 30 and 39 years, 105 (35.0%) were between 40 and 49 years, and 63 (21.0%) were 50 years or older. With respect to educational attainment, 57 respondents (19.0%) held a bachelor's degree, 168 (56.0%) held a master's degree, and 75 (25.0%) held a doctoral degree. The professional-experience distribution showed that 48 participants (16.0%) had less than 5 years of relevant experience, 81 (27.0%) had 5–10 years, 96 (32.0%) had 11–15 years, and 75 (25.0%) had more than 15 years of

professional experience. Regarding the participants' main occupational or technical field, 93 respondents (31.0%) were engaged in electricity distribution and power-system operation, 54 (18.0%) worked in smart-grid and automation activities, 45 (15.0%) were involved in distributed generation and renewable energy, 39 (13.0%) specialized in artificial intelligence, data analysis, or information technology, 36 (12.0%) worked in energy management and demand-response activities, and 33 (11.0%) were engaged in planning, regulation, consulting, or academic research. Overall, the distribution of educational level, professional experience, and technical expertise indicated that the sample contained a substantial proportion of experienced and highly educated respondents with direct familiarity with the technological, operational, and managerial dimensions of active distribution networks.

Table 1

Descriptive Statistics of the Main Constructs of the Flexibility Management Model

Construct	Number of Items	Mean	SD	Skewness	Kurtosis	Rank
Intelligent data and communication infrastructure	5	4.18	0.56	-0.71	0.64	2
Artificial intelligence capabilities	5	4.22	0.53	-0.76	0.81	1
Forecasting and uncertainty management	5	4.11	0.59	-0.62	0.38	4
Flexible demand management	5	4.07	0.61	-0.54	0.31	6
Distributed-generation coordination	5	4.09	0.58	-0.59	0.44	5
Energy-storage management	4	3.92	0.66	-0.41	0.16	9
Consumer and prosumer participation	5	3.98	0.63	-0.47	0.29	8
Incentive and market mechanisms	4	3.84	0.68	-0.32	-0.08	11
Intelligent decision-making	5	4.12	0.57	-0.64	0.52	3
Network operational flexibility	5	4.04	0.60	-0.51	0.27	7
System-level flexibility outcomes	4	3.89	0.64	-0.38	0.11	10

The descriptive findings presented in Table 1 showed that all dimensions of the proposed flexibility management model received relatively high mean scores, with mean values ranging from 3.84 to 4.22 on the five-point scale. Artificial intelligence capabilities obtained the highest mean score ($M = 4.22$, $SD = 0.53$), indicating that the respondents regarded AI-based analytical, forecasting, optimization, and adaptive decision-support capabilities as the most prominent element of flexibility management in active distribution networks. Intelligent data and communication infrastructure ranked second ($M = 4.18$, $SD = 0.56$), emphasizing the importance of real-time data acquisition, advanced metering, communication interoperability, and digital connectivity as enabling conditions for the effective application of AI. Intelligent decision-making ranked third ($M = 4.12$, $SD = 0.57$), followed by forecasting and uncertainty management ($M = 4.11$, $SD = 0.59$) and distributed-generation

coordination ($M = 4.09$, $SD = 0.58$). These findings suggest that the proposed model is strongly centered on the integration of data infrastructure, AI-enabled forecasting, and coordinated decision-making. Flexible demand management also received a high mean score ($M = 4.07$, $SD = 0.61$), followed by network operational flexibility ($M = 4.04$, $SD = 0.60$) and consumer and prosumer participation ($M = 3.98$, $SD = 0.63$). Energy-storage management ($M = 3.92$, $SD = 0.66$), system-level flexibility outcomes ($M = 3.89$, $SD = 0.64$), and incentive and market mechanisms ($M = 3.84$, $SD = 0.68$) received comparatively lower, although still clearly above-midpoint, scores. The relatively lower mean for incentive and market mechanisms indicates that market-based arrangements, dynamic tariffs, flexibility remuneration, and economic incentives may be less developed in practice than technical and digital capabilities. In addition, all skewness values ranged from -0.76 to -0.32

and all kurtosis values ranged from -0.08 to 0.81, which were within acceptable limits and indicated the absence of severe distributional irregularities among the study constructs.

Thus, the descriptive analysis provided preliminary support for the relevance of all 11 dimensions included in the proposed flexibility management model.

Table 2

Measurement Model Assessment, Reliability, Convergent Validity, Discriminant Validity, and Collinearity

Construct	Loading Range	Cronbach's Alpha	Composite Reliability	AVE	Maximum HTMT	VIF Range
Intelligent data and communication infrastructure	0.734–0.891	0.883	0.915	0.684	0.781	1.62–2.48
Artificial intelligence capabilities	0.761–0.907	0.902	0.928	0.721	0.813	1.74–2.71
Forecasting and uncertainty management	0.728–0.884	0.875	0.910	0.670	0.796	1.59–2.43
Flexible demand management	0.715–0.876	0.861	0.901	0.646	0.772	1.51–2.36
Distributed-generation coordination	0.739–0.895	0.886	0.917	0.689	0.804	1.68–2.57
Energy-storage management	0.752–0.889	0.842	0.894	0.679	0.746	1.47–2.21
Consumer and prosumer participation	0.721–0.881	0.869	0.905	0.657	0.824	1.55–2.64
Incentive and market mechanisms	0.748–0.901	0.857	0.903	0.699	0.768	1.43–2.26
Intelligent decision-making	0.766–0.913	0.908	0.932	0.733	0.836	1.82–2.89
Network operational flexibility	0.743–0.906	0.895	0.924	0.709	0.836	1.79–3.06
System-level flexibility outcomes	0.771–0.918	0.884	0.921	0.744	0.812	1.66–2.73

As shown in Table 2, the measurement model demonstrated satisfactory reliability and validity across all constructs. Standardized indicator loadings ranged from 0.715 to 0.918, and all retained items exceeded the minimum acceptable loading criterion of 0.70. The highest loading was observed among indicators measuring system-level flexibility outcomes, whereas even the lowest loading, observed within the flexible demand management construct, remained above the recommended threshold. Cronbach's alpha coefficients ranged from 0.842 for energy-storage management to 0.908 for intelligent decision-making, thereby exceeding the minimum criterion of 0.70 for all constructs and confirming satisfactory internal consistency. Composite reliability values ranged from 0.894 to 0.932, providing additional evidence that the indicators consistently represented their respective latent variables. Convergent validity was supported because average variance extracted values ranged from 0.646 to 0.744, substantially exceeding the 0.50 criterion. Accordingly, each

latent construct explained more than 50% of the variance in its corresponding measurement indicators. Discriminant validity was examined using the heterotrait-monotrait ratio. The maximum HTMT coefficient associated with each construct ranged between 0.746 and 0.836, with all pairwise values remaining below the conservative threshold of 0.85. This finding indicated that the constructs were empirically distinguishable despite their theoretically related roles in the overall flexibility-management framework. Collinearity was also assessed using variance inflation factors. VIF values ranged from 1.43 to 3.06 and therefore remained well below the threshold of 5, demonstrating that multicollinearity was not sufficiently high to bias the estimation of the structural relationships. Collectively, these results confirmed adequate indicator reliability, internal consistency, convergent validity, discriminant validity, and freedom from problematic collinearity, providing sufficient justification for proceeding to evaluation of the structural model.

Table 3

Structural Path Coefficients of the Proposed Flexibility Management Model

Structural Relationship	β	Standard Error	t	p	Result
Intelligent data and communication infrastructure → Artificial intelligence capabilities	0.624	0.043	14.512	<0.001	Supported
Intelligent data and communication infrastructure → Intelligent decision-making	0.214	0.061	3.508	<0.001	Supported
Artificial intelligence capabilities → Forecasting and uncertainty management	0.671	0.039	17.205	<0.001	Supported
Artificial intelligence capabilities → Intelligent decision-making	0.486	0.055	8.836	<0.001	Supported
Forecasting and uncertainty management → Network operational flexibility	0.219	0.054	4.056	<0.001	Supported
Flexible demand management → Network operational flexibility	0.187	0.051	3.667	<0.001	Supported

Distributed-generation coordination → Network operational flexibility	0.231	0.050	4.620	<0.001	Supported
Energy-storage management → Network operational flexibility	0.143	0.047	3.043	0.002	Supported
Consumer and prosumer participation → Flexible demand management	0.458	0.049	9.347	<0.001	Supported
Incentive and market mechanisms → Consumer and prosumer participation	0.537	0.046	11.674	<0.001	Supported
Intelligent decision-making → Network operational flexibility	0.302	0.052	5.808	<0.001	Supported
Network operational flexibility → System-level flexibility outcomes	0.713	0.036	19.806	<0.001	Supported

The structural-model results presented in Table 3 demonstrated that all hypothesized direct relationships were positive and statistically significant. Intelligent data and communication infrastructure exerted a strong positive effect on artificial intelligence capabilities ($\beta = 0.624$, $t = 14.512$, $p < 0.001$), indicating that the availability of integrated data platforms, smart meters, sensors, communication networks, and interoperable information systems substantially strengthened the capacity of the distribution network to implement AI-based analytical and operational applications. Intelligent data infrastructure also had a significant direct effect on intelligent decision-making ($\beta = 0.214$, $t = 3.508$, $p < 0.001$), suggesting that digital infrastructure contributed to decision quality independently of its indirect contribution through AI capabilities. Artificial intelligence capabilities had a particularly strong effect on forecasting and uncertainty management ($\beta = 0.671$, $t = 17.205$, $p < 0.001$), representing one of the strongest relationships identified in the model. This result showed that machine-learning-based forecasting, pattern recognition, predictive analytics, and real-time processing played a central role in improving the management of uncertainty associated with electricity demand, intermittent renewable generation, and distributed energy resources. Artificial intelligence capabilities also significantly enhanced intelligent decision-making ($\beta = 0.486$, $t = 8.836$, $p < 0.001$), confirming that AI contributed not only to prediction but also to operational optimization and adaptive control.

With respect to the direct determinants of network operational flexibility, intelligent decision-making exhibited the largest standardized direct coefficient ($\beta = 0.302$, $t = 5.808$, $p < 0.001$), demonstrating the importance of adaptive

scheduling, automated optimization, and real-time decision-support mechanisms in converting available flexibility resources into effective network responses. Distributed-generation coordination had the next strongest direct association with operational flexibility ($\beta = 0.231$, $t = 4.620$, $p < 0.001$), followed by forecasting and uncertainty management ($\beta = 0.219$, $t = 4.056$, $p < 0.001$), flexible demand management ($\beta = 0.187$, $t = 3.667$, $p < 0.001$), and energy-storage management ($\beta = 0.143$, $t = 3.043$, $p = 0.002$). The significance of all five paths indicated that flexibility was not produced by a single technological resource; rather, it resulted from the coordinated operation of predictive intelligence, controllable demand, distributed generation, energy storage, and intelligent decision processes. Furthermore, incentive and market mechanisms had a strong positive effect on consumer and prosumer participation ($\beta = 0.537$, $t = 11.674$, $p < 0.001$), and consumer and prosumer participation subsequently affected flexible demand management ($\beta = 0.458$, $t = 9.347$, $p < 0.001$). These relationships indicated that the contribution of end users to distribution-network flexibility depended substantially on the availability of appropriate economic incentives, participation mechanisms, and compensation arrangements. Finally, network operational flexibility exerted the strongest final-stage effect in the structural model on system-level flexibility outcomes ($\beta = 0.713$, $t = 19.806$, $p < 0.001$), showing that improved operational flexibility was strongly associated with enhanced capability to manage peak demand, accommodate renewable generation, reduce congestion, maintain voltage conditions, respond to uncertainty, and increase overall network resilience and efficiency.

Table 4

Explanatory Power, Predictive Relevance, Effect Sizes, and Overall Model Assessment

Endogenous Construct / Model Criterion	R ²	Adjusted R ²	Q ²	Principal Predictor	f ² of Principal Predictor	Interpretation
Artificial intelligence capabilities	0.389	0.387	0.276	Intelligent data and communication infrastructure	0.637	Large effect
Forecasting and uncertainty management	0.450	0.448	0.307	Artificial intelligence capabilities	0.819	Large effect

Consumer and prosumer participation	0.288	0.286	0.193	Incentive and market mechanisms	0.404	Large effect
Flexible demand management	0.372	0.368	0.241	Consumer and prosumer participation	0.265	Medium effect
Intelligent decision-making	0.521	0.518	0.365	Artificial intelligence capabilities	0.303	Medium effect
Network operational flexibility	0.684	0.678	0.472	Intelligent decision-making	0.137	Small-to-medium effect
System-level flexibility outcomes	0.508	0.506	0.371	Network operational flexibility	1.033	Large effect
SRMR	—	—	—	—	0.061	Acceptable model fit
NFI	—	—	—	—	0.917	Acceptable model fit

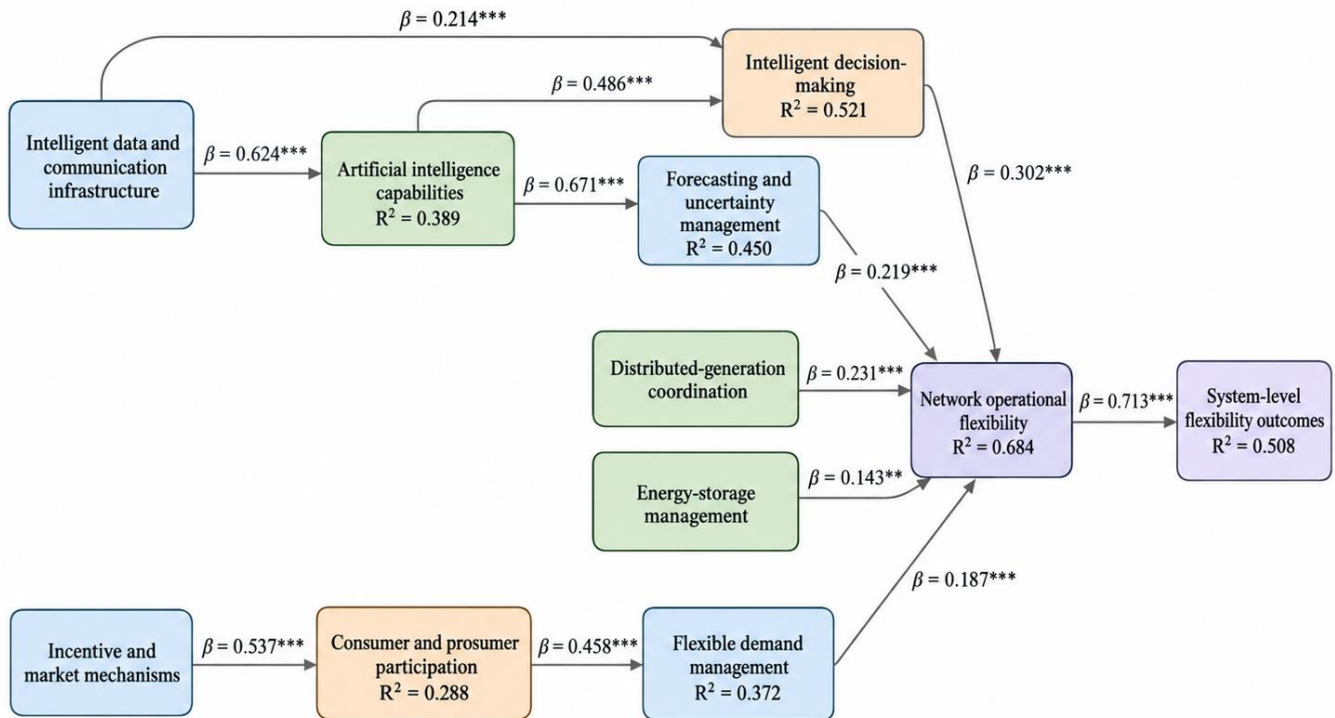
The results in Table 4 further supported the explanatory and predictive adequacy of the proposed model. The coefficient of determination for artificial intelligence capabilities was $R^2 = 0.389$, indicating that approximately 38.9% of its variance was explained by intelligent data and communication infrastructure. The model explained 45.0% of the variance in forecasting and uncertainty management and 52.1% of the variance in intelligent decision-making, reflecting the substantial role of AI capabilities and digital infrastructure in supporting predictive and operational intelligence. Incentive and market mechanisms explained 28.8% of the variance in consumer and prosumer participation, while the antecedent variables of flexible demand management jointly accounted for 37.2% of its variance. Most importantly, the combined predictors of network operational flexibility explained 68.4% of its variance, demonstrating substantial explanatory power for the central endogenous construct of the model. Network operational flexibility subsequently explained 50.8% of the variance in system-level flexibility outcomes. The adjusted R^2 values were very close to the corresponding R^2 values, indicating that the explanatory performance of the model was not artificially inflated by the number of predictors.

The Stone-Geisser Q^2 values were positive for all endogenous constructs and ranged from 0.193 to 0.472, confirming predictive relevance throughout the model. The largest Q^2 value was obtained for network operational flexibility ($Q^2 = 0.472$), indicating particularly strong out-of-sample predictive relevance for the central operational construct. System-level flexibility outcomes also showed

substantial predictive relevance ($Q^2 = 0.371$), followed by intelligent decision-making ($Q^2 = 0.365$) and forecasting and uncertainty management ($Q^2 = 0.307$). Examination of the f^2 effect sizes showed that intelligent data and communication infrastructure had a large contribution to artificial intelligence capabilities ($f^2 = 0.637$), AI capabilities had a large effect on forecasting and uncertainty management ($f^2 = 0.819$), and incentive and market mechanisms had a large effect on consumer and prosumer participation ($f^2 = 0.404$). The effect of consumer and prosumer participation on flexible demand management was moderate ($f^2 = 0.265$), while the contribution of AI capabilities to intelligent decision-making was also moderate ($f^2 = 0.303$). Although the individual effect size of intelligent decision-making on network operational flexibility was comparatively smaller ($f^2 = 0.137$), the combination of forecasting, demand-side flexibility, distributed generation, storage, and intelligent decision-making produced a substantial overall R^2 of 0.684 for operational flexibility. The effect of network operational flexibility on system-level outcomes was particularly large ($f^2 = 1.033$), further demonstrating that operational flexibility represented the principal mechanism through which the model generated system-level benefits. Finally, the standardized root mean square residual was 0.061, which was below the commonly accepted threshold of 0.08, and the normed fit index was 0.917. These indices provided additional evidence that the proposed structural model adequately represented the empirical relationships observed in the data.

Figure 1

Final Structural Model of Artificial Intelligence-Based Flexibility Management in Active Distribution Networks with Consumer and Producer Participation



The final structural model illustrated the integrated mechanism through which technological, behavioral, market, and operational components contributed to flexibility management in active distribution networks. At the upstream level, intelligent data and communication infrastructure functioned as the principal technological foundation of the model and directly strengthened both artificial intelligence capabilities and intelligent decision-making. AI capabilities, in turn, substantially improved forecasting and uncertainty management and contributed directly to intelligent operational decision-making. A separate participation pathway was observed in which incentive and market mechanisms increased consumer and prosumer participation, which subsequently strengthened flexible demand management. At the operational level, forecasting and uncertainty management, flexible demand management, distributed-generation coordination, energy-storage management, and intelligent decision-making simultaneously contributed to network operational flexibility. Among these direct operational antecedents, intelligent decision-making showed the strongest standardized coefficient, followed by distributed-generation

coordination, forecasting and uncertainty management, flexible demand management, and energy-storage management. Network operational flexibility subsequently exerted a strong positive influence on system-level flexibility outcomes. Thus, the final model demonstrated that artificial intelligence should not be regarded as an isolated technical tool; rather, its contribution to active distribution-network flexibility depended on the integration of digital infrastructure, predictive analytics, distributed energy-resource coordination, responsive demand, storage systems, economic incentives, and active participation by consumers and producers. The magnitude and statistical significance of the estimated paths, together with the reliability and validity indices, the substantial R^2 value for network operational flexibility, the positive Q^2 values, and the acceptable overall model-fit indices, collectively confirmed the empirical adequacy of the proposed AI-based flexibility management model.

4. Discussion and Conclusion

The present study aimed to design and validate an artificial intelligence-based flexibility management model

for active distribution networks with the participation of consumers and producers. The findings showed that the proposed model possessed acceptable measurement and structural characteristics and that all hypothesized relationships were statistically significant. At the descriptive level, artificial intelligence capabilities obtained the highest mean score among the model dimensions, followed by intelligent data and communication infrastructure, intelligent decision-making, forecasting and uncertainty management, and distributed-generation coordination. This pattern indicates that experts and practitioners perceived AI-related analytical capabilities and the digital infrastructure necessary to support them as the most central foundations of flexibility management. Such a finding is consistent with the broader technological transformation of electricity distribution systems, in which conventional passive network management is increasingly being replaced by data-driven, adaptive, and intelligent approaches. Previous studies in electricity distribution contexts have emphasized that organizational and operational performance depends not only on physical assets but also on managerial, environmental, and technological conditions (Bahrini et al., 2015; Pourabadolahankooch et al., 2021). In this regard, the present findings extend previous evidence by showing that digital infrastructure and AI capabilities can be conceptualized as interconnected antecedents of flexibility-oriented performance.

The first important structural finding was that intelligent data and communication infrastructure had a strong positive effect on artificial intelligence capabilities. This result suggests that AI cannot create operational value independently of reliable data acquisition, communication connectivity, smart metering, interoperability, and real-time information exchange. Machine-learning algorithms, predictive models, and intelligent optimization systems require continuous access to high-quality and sufficiently granular data. In active distribution networks, these data may include electricity consumption, distributed generation output, equipment status, storage availability, network loading, voltage profiles, weather conditions, prices, and consumer response patterns. Therefore, deficiencies in communication infrastructure, fragmented information systems, or low data quality can directly weaken the analytical and predictive capacity of AI. This interpretation is compatible with research showing the importance of identifying dynamic consumption patterns through data-driven analytical methods (Zhang et al., 2021). The ability to classify and predict electricity-consumption behavior is

fundamentally dependent on the availability of detailed and reliable information, and such information becomes even more critical when flexibility must be managed in real time.

Intelligent data and communication infrastructure also had a statistically significant direct effect on intelligent decision-making. This finding indicates that information infrastructure supports decision quality not only indirectly through AI but also by improving situational awareness, information accessibility, and coordination among network actors. In complex distribution systems, operational decisions regarding congestion, voltage control, demand response, distributed generation, and energy storage require timely access to network conditions. This result is conceptually consistent with previous studies of electricity distribution organizations that have emphasized the importance of institutional and managerial capacity in improving performance. For example, studies in Iranian electricity distribution companies have shown that external environmental conditions, organizational culture, risk-management approaches, and institutional arrangements influence operational outcomes (Bahrini et al., 2015; Rezaei Dizgah et al., 2022; Valizadeh & Hosseini, 2010). The present study adds a digital dimension to this body of evidence by demonstrating that intelligent decision-making increasingly depends on integrated information infrastructure.

Another major finding was that artificial intelligence capabilities had a very strong positive effect on forecasting and uncertainty management. This was one of the strongest relationships in the structural model. The result is theoretically plausible because active distribution networks are characterized by uncertainty originating from renewable energy variability, dynamic demand, prosumer behavior, storage availability, and unexpected operational conditions. Artificial intelligence can improve the forecasting of these variables through machine learning, pattern recognition, and adaptive predictive models. The findings of Zhang et al. support this interpretation by demonstrating that advanced analytical approaches can reveal heterogeneous and dynamic electricity-consumption patterns (Zhang et al., 2021). From a flexibility-management perspective, more accurate prediction of consumption and production makes it possible to identify where and when flexibility will be required and which resources are most suitable for activation. Thus, AI can transform uncertainty from a largely reactive operational problem into a manageable forecasting and optimization problem.

Artificial intelligence capabilities also exerted a significant positive effect on intelligent decision-making. This result confirms that the contribution of AI extends beyond forecasting. AI-based systems can support prioritization of alternatives, real-time optimization, automated control, resource scheduling, anomaly detection, and adaptive decision-making. The result also resembles findings from consumer-oriented research showing that AI can substantially influence decision processes by processing information, personalizing options, and improving the relevance of recommendations (Ho & Chow, 2023; Manikandan & Bhuvaneswari, 2024). Although those studies focus on consumer decisions rather than power-system operations, they support the broader proposition that AI changes how decisions are generated and acted upon. Research has also shown that AI can shape engagement and behavioral responses by improving perceived relevance and value (Amin, 2025; Rather, 2025). Applied to electricity networks, these capabilities can facilitate more adaptive interaction between the distribution operator and flexible resources.

The findings further revealed that intelligent decision-making had the strongest direct effect among the immediate predictors of network operational flexibility. This is an important result because it indicates that the availability of flexible resources alone is insufficient. Their value depends on the quality of decisions governing when, where, and how they are activated. Operational flexibility requires the simultaneous consideration of technical constraints, resource availability, demand patterns, renewable generation, storage conditions, and network requirements. Therefore, intelligent decision-making serves as the mechanism through which information and AI capabilities are converted into actionable flexibility. This interpretation is consistent with previous studies indicating that performance improvement in electricity distribution systems requires coordinated managerial and operational processes rather than isolated technical interventions (Fallahi et al., 2019; Pourabadolahankooch et al., 2021).

Distributed-generation coordination also had a significant positive effect on network operational flexibility. This finding confirms that active management of decentralized generation sources is an essential component of flexible distribution networks. Distributed generation can reduce network stress and support local balancing when properly coordinated, but uncontrolled or poorly forecast generation may create voltage problems, reverse power flows, or local congestion. Therefore, flexibility does not arise merely from

increasing the amount of distributed generation; it depends on the capacity to coordinate such resources according to network conditions. This result is consistent with the broader emphasis on resilience and adaptive operation in electricity distribution systems. Previous research on the resilience of electricity distribution companies has highlighted the importance of strengthening the ability of the network to respond to disturbances and changing operational conditions (Karami & Separi, 2016). Coordinated distributed generation can contribute to such resilience by increasing the range of operational responses available to the network.

Forecasting and uncertainty management had another significant positive effect on network operational flexibility. This finding demonstrates that flexibility is closely linked to anticipation. A distribution system that can accurately predict demand, distributed generation, and network conditions is better positioned to schedule flexible resources before operational problems occur. By contrast, poor forecasting increases the likelihood that flexibility will be activated too late, in insufficient quantities, or in inappropriate locations. This finding reinforces the role of AI-based predictive capabilities identified earlier in the model and supports the argument that active distribution-network management should shift from reactive intervention toward anticipatory control. It also aligns with studies emphasizing the importance of organizational risk management in electricity distribution companies (Valizadeh & Hosseini, 2010), because forecasting and uncertainty management essentially extend risk-management principles into real-time operational decision-making.

Flexible demand management also showed a significant positive relationship with network operational flexibility. This result confirms that the demand side should be treated as an active operational resource rather than merely as an exogenous load. When consumers can shift, reduce, or reschedule electricity consumption, network operators gain an additional mechanism for responding to congestion, peak demand, renewable-generation fluctuations, and capacity constraints. The finding is particularly important because demand-side flexibility often requires lower capital investment than physical network expansion. However, its effectiveness depends heavily on consumer willingness and participation. The significant path identified from consumer and prosumer participation to flexible demand management confirms this relationship and indicates that demand flexibility cannot be managed successfully without active involvement from end users.

The positive effect of consumer and prosumer participation on flexible demand management is strongly consistent with the findings of Abdelmotteleb et al., who emphasized the importance of customer engagement in distribution-level flexibility product provision (Abdelmotteleb et al., 2022). Consumers and prosumers can provide flexibility through load shifting, demand reduction, distributed generation, storage, and participation in flexibility markets, but the practical availability of these resources depends on willingness to engage. The present result is also supported indirectly by studies of technology adoption and consumer behavior. Jayasingh et al. showed that technology adoption depends on a combination of behavioral and technological factors (Jayasingh et al., 2022), while Gupta and Mukherjee demonstrated that consumer behavior can change substantially in response to evolving digital and environmental conditions (Gupta & Mukherjee, 2022). These findings imply that electricity consumers are not passive actors and that their participation can be shaped by the design of digital platforms, incentives, information, and perceived value.

The study also found that incentive and market mechanisms had a strong positive effect on consumer and prosumer participation. This finding is particularly important because it shows that participation is not likely to occur solely because the technology exists. Consumers and producers must perceive economic or functional value in making their flexibility available. Appropriate remuneration, dynamic pricing, flexibility contracts, local energy markets, demand-response incentives, and transparent participation rules can substantially increase engagement. This interpretation is consistent with consumer-behavior research showing that perceived value and personalized benefits influence engagement with AI-enabled technologies (Rather, 2025). Studies in digital commerce have similarly shown that AI affects consumer behavior by influencing perceived relevance, convenience, and decision processes (Aggarwal et al., 2024; Amin, 2025; Manikandan & Bhuvaneswari, 2024). Although electricity flexibility differs from retail consumption, the underlying behavioral mechanism is comparable: participation increases when individuals perceive meaningful value and when the interaction mechanism is simple, relevant, and responsive to their needs.

Energy-storage management was also found to contribute significantly to network operational flexibility, although its standardized coefficient was smaller than those of several other operational predictors. This may reflect the fact that

storage provides substantial technical flexibility but that its effectiveness depends on capacity, state of charge, ownership, location, and coordinated scheduling. Energy storage can absorb excess renewable generation, shift electricity across time, reduce peak loads, support voltage control, and provide reserve capacity. However, these benefits are maximized when storage is integrated with forecasting and intelligent control. Thus, the relatively smaller direct effect does not imply that storage is unimportant; rather, it suggests that storage is one component of a broader flexibility portfolio whose value is enhanced by AI-enabled coordination.

The final and strongest downstream relationship showed that network operational flexibility had a substantial positive effect on system-level flexibility outcomes. This finding confirms the central theoretical proposition of the model: when a distribution network can coordinate demand, distributed generation, storage, forecasting, and intelligent decision-making, it achieves broader improvements in its ability to respond to changing conditions. Such outcomes include better peak-load management, reduced congestion, enhanced accommodation of distributed renewable generation, improved resilience, and more efficient use of existing network assets. This result is compatible with previous evidence on electricity-distribution efficiency and resilience, which emphasizes the need for integrated management of technical and organizational resources (Fallahi et al., 2019; Karami & Separi, 2016). It also aligns with sustainability-oriented management approaches that advocate the integration of economic, operational, and environmental performance rather than reliance on isolated performance indicators (Fernández-González et al., 2023).

The explanatory power of the model was also noteworthy. Approximately 68.4% of the variance in network operational flexibility and 50.8% of the variance in system-level flexibility outcomes were explained by the model. These values indicate that the proposed framework captures a substantial proportion of the mechanisms underlying flexibility management. Moreover, positive Q^2 values for all endogenous constructs confirmed predictive relevance, while the acceptable SRMR and NFI values supported overall model adequacy. From a managerial perspective, the results imply that flexibility management should not be approached as a purely engineering problem. Organizational culture, workforce capability, interorganizational collaboration, and sustainability orientation remain important conditions for implementing technological solutions effectively. Previous studies in Iranian electricity

distribution organizations have highlighted the relevance of organizational culture, strategic human-resource management, university-industry cooperation, and green human-resource practices (Moghaddas Nodeh, 2019; Rezaei Dizgah et al., 2022; Samavi, 2021; Yahya Pour et al., 2022). Likewise, the increasing use of AI may alter employee roles and competency requirements, creating a need for workforce adaptation and reskilling (Fan, 2024). Therefore, the proposed model should be understood as a socio-technical framework in which AI, physical network resources, market incentives, consumer participation, and organizational capability operate jointly rather than independently.

The present study had several limitations that should be considered when interpreting its findings. First, the quantitative phase was conducted among managers, engineers, specialists, and experts located in Tehran, which may limit the generalizability of the results to electricity distribution companies operating in provinces with different network structures, climatic conditions, levels of digital maturity, or consumer characteristics. Second, although the model incorporated consumer and prosumer participation as a central construct, the quantitative respondents were predominantly professionals and technical experts rather than ordinary residential consumers or small-scale producers themselves. Consequently, assessments of participation and behavioral mechanisms were based largely on expert perceptions. Third, the cross-sectional design did not permit examination of changes in flexibility performance over time or after actual deployment of AI-based flexibility systems. Fourth, the study relied on self-reported questionnaire data, which may be affected by common-method variance, professional optimism, or socially desirable responses. Fifth, the model focused primarily on managerial, technological, behavioral, and operational relationships and did not explicitly simulate physical power flows, feeder-level voltage constraints, cybersecurity threats, or real-time market clearing. Finally, although the structural model showed strong explanatory and predictive indicators, the model should be interpreted as an empirically validated management framework rather than as a substitute for engineering validation through operational network simulations.

Future studies should validate the proposed model in other provinces, distribution companies, and national electricity systems to determine the stability of the identified relationships across different regulatory, technological, and socioeconomic environments. Longitudinal and experimental designs would be particularly valuable for

examining how flexibility performance changes before and after implementation of AI-based forecasting, demand response, and distributed-resource coordination systems. Future research should also collect primary data directly from residential consumers, commercial users, prosumers, aggregators, and distributed generators to compare their perceptions with those of technical experts and managers. Integrating the present structural model with power-system simulation environments would allow researchers to examine whether improvements in managerial and behavioral constructs translate into measurable reductions in congestion, losses, voltage deviations, renewable curtailment, and peak demand. Further studies could also incorporate cybersecurity, data governance, algorithmic transparency, privacy, trust in automated control, and regulatory readiness as additional model dimensions. Comparative evaluation of different artificial intelligence techniques, including machine learning, deep learning, reinforcement learning, and multi-agent optimization, could identify which methods are most appropriate for specific flexibility-management functions. Finally, future research could investigate moderating variables such as network digital maturity, renewable-energy penetration, ownership structure, tariff design, consumer digital literacy, and organizational readiness.

Electricity distribution companies should treat flexibility management as an integrated strategic capability rather than as a collection of independent technical projects. Managers should prioritize investment in interoperable data platforms, advanced metering infrastructure, secure communication networks, and real-time monitoring because these systems provide the information foundation required for effective AI applications. Distribution companies should establish dedicated analytical and flexibility-management units capable of combining expertise in power systems, data science, artificial intelligence, consumer behavior, and market design. AI systems should initially be deployed in high-value applications such as load forecasting, renewable-generation forecasting, flexibility-resource identification, congestion prediction, and coordinated scheduling of distributed resources. At the same time, operators should develop transparent incentive mechanisms that financially reward consumers and prosumers for providing measurable flexibility. Participation processes should be simple, digitally accessible, and supported by personalized information so that users can understand both the benefits and obligations associated with flexibility programs. Distribution companies should also invest in staff training

and reskilling to ensure that engineers and managers can interpret AI outputs, supervise automated decisions, and intervene appropriately when abnormal conditions occur. Pilot projects should be implemented in selected feeders before large-scale deployment, with performance evaluated using operational, economic, environmental, consumer, and resilience indicators. Finally, regulatory authorities should support the development of standardized flexibility products, data-sharing protocols, consumer-protection rules, and compensation mechanisms so that AI-enabled flexibility can develop within a clear and trustworthy institutional framework.

Authors' Contributions

Authors contributed equally to this article.

Declaration

In order to correct and improve the academic writing of our paper, we have used the language model ChatGPT.

Transparency Statement

Data are available for research purposes upon reasonable request to the corresponding author.

Acknowledgments

We would like to express our gratitude to all individuals helped us to do the project.

Declaration of Interest

The authors report no conflict of interest.

Funding

According to the authors, this article has no financial support.

Ethics Considerations

In this research, ethical standards including obtaining informed consent, ensuring privacy and confidentiality were considered.

References

Abdelmotteleb, I., Fumagalli, E., & Gibescu, M. (2022). Assessing customer engagement in electricity distribution-level flexibility product provision: The Norwegian case.

- Sustainable Energy, Grids and Networks*, 29, 100564. <https://doi.org/10.1016/j.segan.2021.100564>
- Aggarwal, D., Sharma, D., & Saxena, A. B. (2024). Enhancing the Online Shopping Experience of Consumers Through Artificial Intelligence. *International Journal of Information Technology and Computer Engineering*(42), 1-5. <https://doi.org/10.55529/ijitc.42.1.5>
- Amin, A. (2025). Artificial Intelligence in Social Media: A Catalyst for Impulse Buying Behavior? *Young Consumers Insight and Ideas for Responsible Marketers*. <https://doi.org/10.1108/yc-10-2024-2297>
- Bahrini, M., Nikpei, M., & Baharvand, B. (2015). The impact of external environment on performance management in Lorestan Province Electricity Distribution Company. 3rd International Conference on Modern Research in Management, Economics, and Accounting.
- Fallahi, A., Fallahi, F. A. U. S. H., Ghaderi, S. F., & Ebrahimi, R. (2019). Application of a robust data envelopment analysis model for performance evaluation of electricity distribution companies. *International Journal of Energy Sector Management*, 15(4), 724-742. <https://doi.org/10.1108/IJESM-08-2018-0008>
- Fan, X. (2024). Artificial Intelligence's Impact on Employment: Challenges, Potential Consumers, and Policy Responses Through Automation and Workforce Rehabilitating. *Lecture Notes in Education Psychology and Public Media*, 73(1), 50-55. <https://doi.org/10.54254/2753-7048/73/20241040>
- Fernández-González, R., Puime-Guillén, F., & Vila-Biglieri, J. E. (2023). Environmental strategy and the petroleum industry: a sustainability balanced scorecard approach. *Journal of Petroleum Exploration and Production Technology*, 13(2), 763-774. <https://doi.org/10.1007/s13202-022-01543-9>
- Gupta, A. S., & Mukherjee, J. (2022). Long-term changes in consumers' shopping behavior post-pandemic: An exploratory study. *International Journal of Retail and Distribution Management*, 50(12), 1518-1534. <https://doi.org/10.1108/IJRDM-04-2022-0111>
- Ho, S. P. S., & Chow, M. Y. C. (2023). The Role of Artificial Intelligence in Consumers' Brand Preference for Retail Banks in Hong Kong. *Journal of Financial Services Marketing*, 29(2), 292-305. <https://doi.org/10.1057/s41264-022-00207-3>
- Jayasinh, S., Choy, S. L., & Lee, S. (2022). Consumers' adoption of online shopping technologies: An integrated perspective. *International Journal of Retail & Distribution Management*, 50(4), 401-422.
- Karami, M. A., & Separi, F. (2016). Durability and Resiliency Improvement in Mazandaran Electricity Distribution Company Against Storm. 91 (94).91 (94). <https://doi.org/10.1049/cp.2016.0691>
- Manikandan, G., & Bhuvaneshwari, G. (2024). Measuring the Influence of Artificial Intelligence (AI) on Online Purchase Decisions-in Case of Indian Consumers. *International Journal of Scientific Research in Science Engineering and Technology*, 250-259. <https://doi.org/10.32628/ijrsrset2411122>
- Moghaddas Nodeh, M. (2019). Investigating challenges of university-industry collaboration: Case study of Tehran Province Electricity Distribution Company. *Innovation Management*, 8(1), 8-106.
- Pourabadolahankooch, M., Nowbahar, E., Sajoodi, S., & Khalafi, R. (2021). Efficiency and scale: Evidence from electricity distribution companies in Iran. *Iranian Journal of Energy Economics*, 10(39), 71-97. https://jtee.atu.ac.ir/article_14274.html
- Rather, R. A. (2025). Does Consumers' Reveal Engagement Behaviours in Artificial Intelligence (AI)-Based

- Technologies? The Dynamics of Perceived Value and Self-Congruence. *International Journal of Hospitality Management*, 126, 103989. <https://doi.org/10.1016/j.ijhm.2025.103989>
- Rezaei Dizgah, M., Ajali, M., & Homayounfar, M. (2022). The effect of organizational culture on the safety performance of employees of Guilan Province Electricity Distribution Organization. *Journal of Occupational Health and Health Promotion*, 6(2), 98-110. <https://doi.org/https://doi.org/10.18502/ohhp.v6i2.10298>
- Samavi, H. (2021). Strategic Factors of Efficient Human Resource Management in Iranian Electricity Distribution Companies. The First International Conference on the Leap of Management Sciences, Economics, and Accounting, Sari,
- Valizadeh, M., & Hosseini, S. H. (2010). A project-based model for the growth of organizational risk management in electricity distribution companies. In Fifteenth National Conference on Electricity Distribution Networks,
- Yahya Pour, M., Tabari, M., Mehrara, A., Bagherzadeh, M., & Baloei Jamkhaneh, E. (2022). Designing a Green Human Resource Management Excellence Model in Northern Iran's Electricity Distribution Companies. *Ethical Research Quarterly*, 12(4), 278-304.
- Zhang, Y., Ai, Q., & Li, Z. (2021). Grouping of Dynamic Electricity Consumption Behaviour: An *f*-divergence Based Hierarchical Clustering Model. *Iet Generation Transmission & Distribution*, 15(22), 3164-3175. <https://doi.org/10.1049/gtd2.12248>