

Digital Transformation in the Energy Sector Using Internet of Things Artificial Intelligence and Machine Learning Solutions

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ABSTRACT

To increase energy efficiency . reduce losses . support the integration of renewable energy sources , and improve the performance of smart grids, the digital transformation of the energy sector is essential . This research paper examines the role of machine learning (ML), artificial intelligence (AI), and the Internet of Things (IoT) in accelerating the digital transformation of smart energy systems. The study explores how IoT-enhanced monitoring and sensor-based automation can enhance the accuracy of machine learning-based decisions in smart grids and smart meters. The study employed a questionnaire-based research methodology , distributing data to 113 participants from the energy sector . SPSS software and structural equation modeling (SEM) were used for data analysis. The results showed good agreement with factor analysis, with a Kaiser-Meier-Olkin (KMO) index of 0.894 and a statistically significant Bartlett test result . The survey also demonstrated very good internal reliability with a Cornbrash's alpha coefficient of (0.943) The structural model results showed that enabling factors had the greatest impact on the behavioral intention to adopt smart energy technologies ($FC \rightarrow BI = 0.791$) followed by effort expectations ($EE \rightarrow BI = 0.661$) then performance expectations ($PE \rightarrow BI = 0.617$) and at last social influence ($SI \rightarrow BI = 0.457$) . The success of implementing the Internet of Things and artificial intelligence in the energy sector depends not only on technical work but also on user support and infrastructure readiness, as clearly demonstrated by the research findings. By linking technology acceptance factors with smart energy technologies. this research offers practical applications for smart grid developers and organizations working to accelerate digital transformation .

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1. Introduction

The introduction Highlights the importance of artificial intelligence the Internet of Things and machine learning in modern smart systems, as well as the evolution of industrial revolutions. It also focuses on communication technologies for automation and control in smart homes and sensor devices . Furthermore , the introduction discusses the role of machine learning in digital control within the energy sector , mitigating environmental impacts and promoting energy efficiency .

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2. Related Work

2.1. *IoT and smart energy infrastructure*

Smart energy systems capable of supporting the Internet of Things (IoT) rely on connected sensors, intelligent intermediaries, operators, corridors, and communication platforms. These components collect operational data from residential, industrial, and utilities, and transmit it to local computing systems, both within and beyond the building's boundaries. This infrastructure enables real-time monitoring, remote control, and intelligent decision-making. In smart buildings, IoT devices monitor lighting, heating, ventilation, air conditioning, functionality, security, and equipment usage. This information can be used to reduce excessive consumption, increase comfort, and improve proactive operations. In smart grids, IoT enhances the overall visibility of distribution networks, allowing utility companies to detect faults, identify abnormal consumption, and improve resource management. Recent studies have highlighted the importance of IoT for promoting decentralized energy systems, microgrids, and the integration of renewable energy sources and intelligent intermediaries. IoT platforms connect consumers, distributed active resources, storage systems, and red operators in a unified digital ecosystem. However, the proliferation of IoT presents challenges related to compatibility, cybersecurity, data privacy, escalation, and standards. From an adoption perspective, IoT architecture must be viable and beneficial. If users and organizations recognize that IoT devices improve control and reduce power consumption, expected performance will increase. If systems are easy to use and benefit from appropriate configuration and infrastructure, expected effort levels and expected conditions will improve. Therefore, continue to consider the technology throughout the day in its technical design.

2.2. *Artificial intelligence and machine learning in smart grids*

Artificial intelligence and machine learning techniques are widely used to transform raw energy data into predictive and advisory insights. Common applications include load forecasting, renewable energy production forecasting, non-technical loss detection, equipment troubleshooting, anomaly monitoring, information security, demand response enhancement, and heating and cooling system management. These applications help improve operational efficiency and strategic planning. Artificial neural networks support vector machines decision trees, random forests, reinforcement learning (R&D), deep learning (D&S) recurrent neural networks and convolutional neural networks have been used in energy research. These models are effective because they can recognize complex nonlinear relationships that are difficult to represent using traditional statistical methods. For example, machine learning models can learn consumption patterns from historical data and predict both short-term and long-term energy demand. Recent research published between 2023 and 2025 indicates that AI-enhanced energy management systems can enhance grid resilience, integrate volatile renewable energy production, and optimize distributed energy resources. Systematic studies have highlighted the growing role of artificial intelligence and machine learning in enhancing reliability, cyber security resilience, and energy market operations. These developments underscore the importance of current research and justify the inclusion of recent studies in the revised edition. Despite these benefits, the application of AI & ML faces challenges such as a shortage of high-quality data, difficulty in interpreting it significant computing requirements, and regulatory resistance. Therefore, attracting users and creating the right conditions are crucial for transitioning from experimental models to practical applications in the energy sector.

3. Research Framework

3.1. *Statement of problem*

Through automation, remote monitoring, and efficient energy management using connected devices and sensors, and by enhancing security, the Internet of Things (IoT), artificial intelligence (AI), and machine learning (ML) are supporting both smart grids and smart buildings. Improving energy efficiency and integrating renewable energy are essential for mitigating the effects of climate change and achieving sustainable development.

3.2. *Importance of research*

The text highlights the role of the Internet of Things in smart buildings and smart grids through connected devices, sensors, and automation. It explains how Artificial Intelligence and Machine Learning improve energy efficiency,

security, and smart energy management by enabling real-time monitoring, data analysis, and automated control systems.

3.3. Research objectives

The objectives considered in this research are categorized as follows:

3.3.1 General Objective

To investigate the digital transformation in the energy sector using IoT, AI, and machine learning solutions

3.3.2 Specific objectives

- 1- To investigate the potential contribution of IoT in the efficient use of energy, reducing energy demand, and increasing the share of renewable energy sources
- 2- To investigate the infrastructure required for installing IoT devices and their components in smart buildings and networks
- 3- To investigate solutions for the application of sensors, mechanical equipment, and electronic devices based on AI, IoT, and smart networks with an approach to optimizing energy consumption.

3.4. Practical goals

- Ministry of Energy
- Companies active in the energy sector
- Companies active in the field of urban and industrial smart infrastructure .

3.5. Research Questions

3.5.1 General Question

What are the applications of modern technologies such as the Internet of Things, artificial intelligence , and machine learning algorithms in smart grids ?

3.5.2 Specific Questions

- 1- What role does the Internet of Things play in optimizing and reducing energy waste in systems deployed in smart buildings ?
- 2- What are the challenges of deploying the Internet of Things in the energy sector ?
- 3- How does the Internet of Things and how does it function in the grid and smart meters with the ability to receive real-time energy data ?

3.6. Research Hypotheses

3.6.1 General Hypothesis

The use of the Internet of Things, artificial intelligence and new machine learning algorithms will create a huge digital transformation in the field of energy in domestic, industrial and commercial uses .

3.6.2 Specific hypotheses

- 1- Advances in the conversion and integration of various types of energy, such as renewable energies , Alongside new forms of communication and information technology , have paved the way for what is known today as smart homes .
- 2- The Internet of Things enables the simultaneous identification, monitoring and remote control of multiple devices , which has wide applications in the supply , transmission, distribution and demand of energy.

3- Home automation systems combined with the Internet of Things, artificial intelligence, Machine learning and big data are promising options that contribute to energy efficiency and effectiveness., greater savings , security and comfort of building occupants and reduce environmental impacts .

3.7.Statistical population

In this study, the statistical population includes all stakeholders and activists in the energy sector who are directly or indirectly affected by the digital transformation . This statistical population can include the Ministry of Energy , energy distribution and transmission companies, renewable energy producers, large energy-consuming industries, as well as energy managers and policymakers . Emphasizing this statistical population is important because the research results can be generalized to the entire energy sector of the country and can be used in macro-decision making and strategic policymaking .

3.8.Research Methodology

- 1- Thorough research and evaluation of the dilemmas and solutions for the network of things in intelligent systems using artificial intelligence and machine learning methods .
- 2- Design of the proposed system
- 3- Design of a questionnaire to obtain the opinions of subject matter experts to evaluate the proposed system
- 4- Analysis and evaluation of the results and identification of the strengths and weaknesses of the proposed system
- 5- Implementation of the proposed system

4.Methods and techniques

4.1. Integrating IoT with machine learning to create a smart grid

In the following sections, the most popular machine learning algorithms that, when paired with IoT, may make the smart grid as energy efficient as possible are explained in detail. Integrating IoT and machine learning technology in smart grids increases energy efficiency, as presented in Figure 1

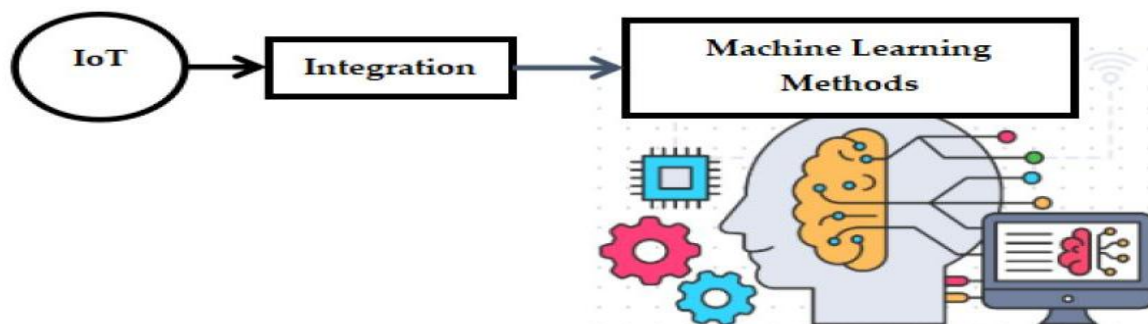


Figure 1: Schematic diagram of the integration of IoT and machine learning technology in smart grids [1]

4.2. Artificial Intelligence-Based Approaches in Smart Grids

In the technical literature a smart structure is defined as one that has automated control systems and uses data to improve design efficiency and occupant comfort and safety . Occupant enjoyment levels, operational efficiency and asset utilization may be significantly enhanced by integrating artificial intelligence into IoT-related structures and devices [2] . By simplifying procedures, generating new information, and increasing the effectiveness of environmental work, we can improve processes enhance environmental performance and independently integrate additional data from IoT sensors and occupant behavior into building systems to generate information.

4.3. Machine Learning in Smart Grid

Studies have demonstrated that smart grid technologies can estimate non-technical losses (NTL) and improve smart meter data accuracy using neural network-based image analysis and anomaly detection techniques that rely on electrical , technical, and GIS data [3] . In addition the SACRB-MAC approach was proposed to enhance throughput and reliability in wireless smart grid communications under poor network conditions, with simulation results confirming its efficient performance [4] . Real-time distributed energy management methods have also been developed using optimization frameworks that depend on current system conditions rather than uncertain future predictions of energy prices, loads, and renewable generation [5][6] . Furthermore, Daisao et al . (2020) improved user privacy by enabling local control of virtual energy management systems and recommended further development of pricing control mechanisms for energy-sharing services [7] . By analyzing trends and supporting adaptive energy control via IoT technologies and smart meter monitoring and managing residential energy consumption, the demand management system with district networks plays a crucial and highly effective role . (Figure 2) illustrates a model of the proposed document management system within an intelligent network environment.

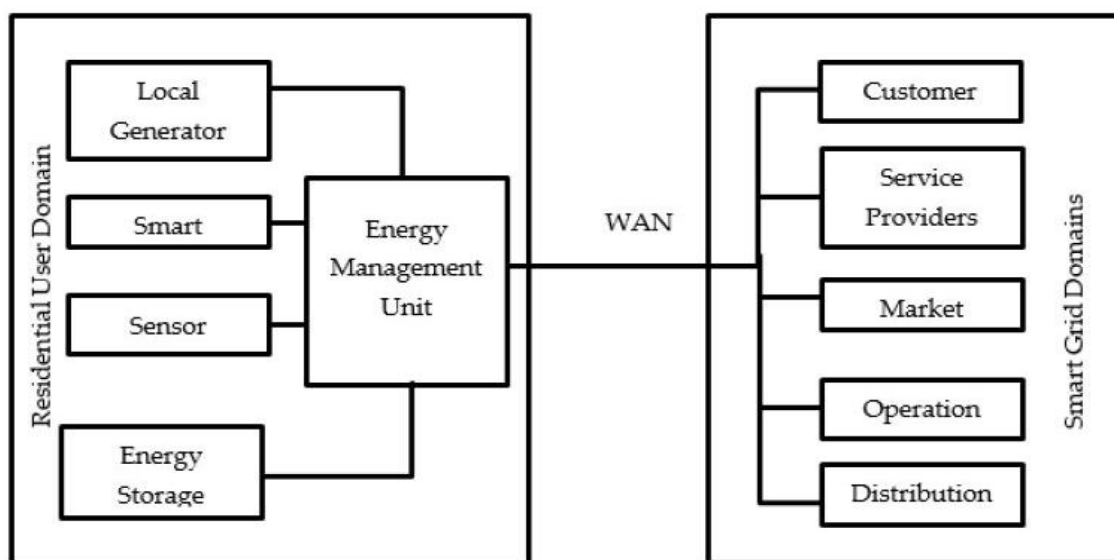


Figure 2: document management system [8]

4.4. Data Mining in Smart Grids

The importance of data science and data mining techniques in analyzing electricity consumption within smart grids has increased as a result of the use of advanced sensors and sophisticated measurement infrastructures [9] . To predict load distribution and improve energy-saving strategies , load aggregation methods have been developed . Based on reliability indicators and aggregation methods , electrical loads are classified into multiple levels [10] . Furthermore the integration of artificial intelligence with Internet of Things technologies has enabled the development of smart energy management services that have the ability to automate processes, increase grid stability and efficiency, and reduce costs [11] . Smart grids , which control and coordinate various smart energy sources , implement AI-powered energy management systems for applications such as electric vehicles, storage units, heating and cooling systems, and renewable energy systems [12][13] . Figure 3 illustrates the role of data mining technologies in smart grid application

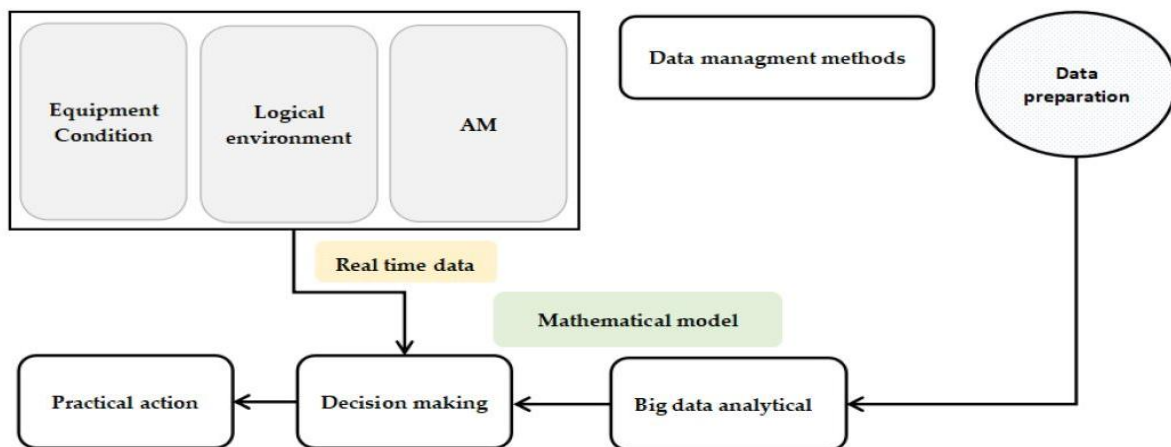


Figure 3: Data mining in smart grids [14]

5. Results and analysis

5.1. Artificial Neural Networks

Smart grid initiatives mainly focus on minimizing energy consumption while improving the comfort and satisfaction of occupants. This is achieved through the deployment of sensors and advanced software that track environmental conditions and enhance energy efficiency. Artificial neural networks (ANNs) are crucial in examining data trends and facilitating various applications, including solar energy management, load forecasting, air conditioning, ventilation systems, and control of power generation [15]. ANN-based models and machine learning methods, such as random forest algorithms and Bayesian neural networks, are employed to assess residential energy usage , forecast future energy needs, and track indoor temperatures in real time [16] . Additionally, the Energy Plus simulation software produces comprehensive datasets that can be used to train ANN models for precise energy consumption analysis [17] . Figure 4 demonstrates the optimization approach based on neural networks within smart grids .

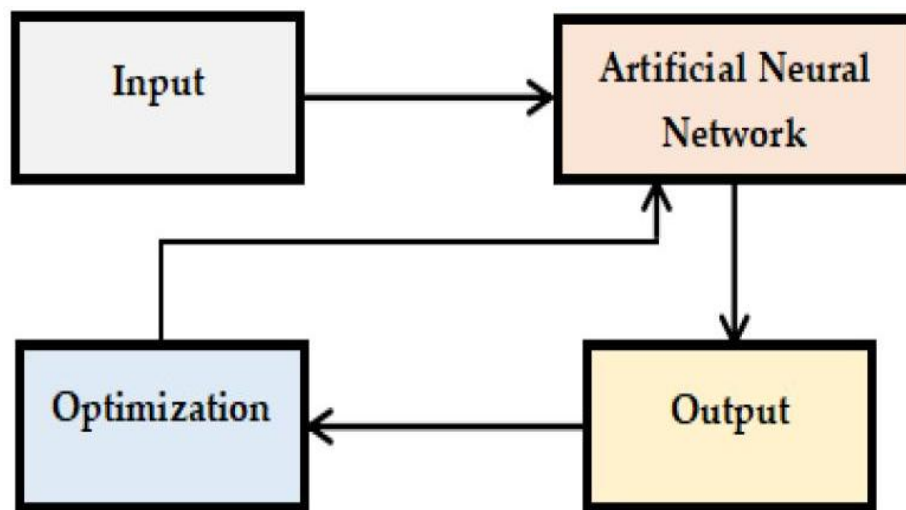


Figure 4: Neural network-based optimization in smart grids

Artificial neural networks necessitate comprehensive training to produce reliable and precise results in smart grid applications , where input signals are examined to assess energy usage and facilitate the implementation of advanced hardware and software systems [18][19] . Smart building technologies also enable users to control electrical appliances through voice commands transmitted via mobile devices using Bluetooth and Wi-Fi connections [20] . To address increasing cyber security risks, intrusion detection systems (IDSs) enhanced with machine learning techniques have been developed for detecting and tracking network threats. A support vector machine (SVM)-based IDS model combined with principal component analysis (PCA) for feature selection was evaluated using different kernel functions, including linear, polynomial, sigmoid, and Gaussian radial basis function (RBF) kernels [21] . Experimental results using the KDD Cup'99 and UNSW-NB15 datasets demonstrated that the Gaussian RBF kernel achieved the highest detection performance with accuracy levels reaching approximately 94% [22] .

5.2. Wavelet Neural Network

Accurate prediction of building energy demand is essential for efficient energy management and environmental sustainability. Wavelet neural networks have been applied to address issues related to temperature, flow , and pressure control, while also improving forecasting accuracy in micro grids and reducing system costs [23] . In addition, wavelet neural networks have enhanced the performance of PID controllers , which are widely used in smart grid control systems for managing lighting, ventilation, temperature, and humidity under varying environmental conditions [24]–[28] . Smart grid communication networks also require efficient protocols suitable for low-power and lossy environments, where devices have limited processing , storage, and energy capabilities [29] . Using multiple performance indicators, including received signal strength, residual power , and data transfer rate , and relying on the fuzzy logic of low-power , loss-prone IPv6 networks , improved routing methods were developed to overcome the limitations of traditional routing methods [30]. Using individual measurement methods improves network reliability and routing efficiency , as demonstrated by simulation results resulting from the integration of these criteria. [31] .

5.3. Machine Learning Algorithms

In intelligent network applications and large-scale data analytics, semi-supervised and unsupervised feature extraction techniques, along with machine learning, play a crucial role . Common methods include deep belief networks (DBNs) , deep Boltzmann machines (DBMs) , convolutional neural networks (CNNs) , recurrent neural networks (RNNs) , decision trees, random forests, support vector machines (SVMs) , and the nearest neighbor algorithm (KNNs) [32][33] . To efficiently process large datasets , the aforementioned methods utilize convolutional and optimization algorithms, although deep learning models generally require large amounts of training data. Figure 5 illustrates the main machine learning algorithms used in intelligent network systems .

5.3.1. Time Series Analysis

In machine learning applications in smart grids it is a crucial element, especially in energy consumption and load prediction . Numerous dimensionality reduction techniques have been developed to improve the analysis of time-series datasets and graphical representation [34] . Researchers have proposed several (time-series-based) solutions for identifying time patterns in smart grid operations [35] . Hybrid models combining fuzzy time series, optimization techniques and supporting vector machines have proven effective in predicting electrical loads [36] . Data-driven methods, such as supporting vector machine models have been widely applied in power estimation and large-scale energy assessment applications [37][38] .

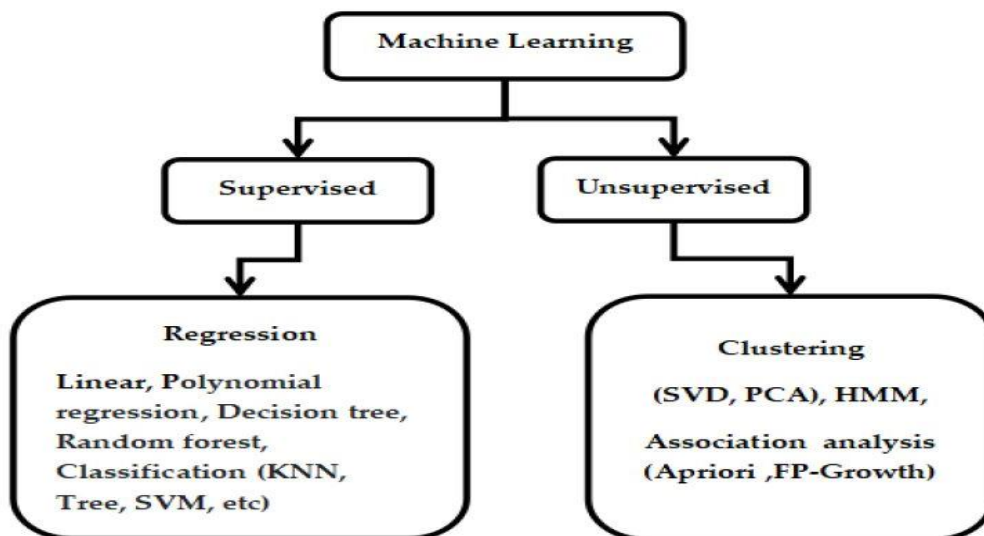


Figure 5: Machine learning algorithms [39]

5.3.2. Regression

Finding the desired function using collected data is the goal of regression analysis. This describes the relationship between variables which is often evaluated in terms of the accuracy of the model's predictions [40] . Three common types of regression analysis are linear regression, ordinary least squares regression, and cross-regression . Researchers used the orthogonal matching seeker regression algorithm to identify the environmental and physical

factors affecting the energy efficiency of smart grids [41] . This study aimed to identify and evaluate the effectiveness of regression models in predicting the energy consumption of commercial buildings. They used data collected from real facilities to facilitate empirical comparisons between different models . The researchers found that regression models performed well compared to other, more complex machine learning models [42] .

6. Inferential Statistics

Inferential statistics and structural equation modeling (SEM) were applied using SPSS statistical software . SEM consists of two main components: the measurement model and the structural model . The measurement model explains how latent variables are measured through observed variables and determines the extent to which observed variables are affected by latent variables and error terms . A higher shared variance between latent and observed variables indicates a stronger contribution of the observed variable in defining the latent construct . Confirmatory factor analysis (CFA) is used to assess the validity and reliability of these constructs . The structural model , on the other hand , illustrates the relationships and effects among latent variables according to the proposed hypotheses. SEM, together with CFA , enables researchers to evaluate relationships among constructs and accept or reject theoretical assumptions. Before conducting factor analysis , the suitability of the data must be verified using the KMO index and Bartlett's test . KMO Index : Measures sampling adequacy and the degree of partial correlation among variables. Values closer to 1 indicate that the data are appropriate for factor analysis . Bartlett's Test : Examines whether significant relationships exist among variables. If the correlation matrix is not an identity matrix , meaningful relationships are present , making factor analysis and the extraction of new factors possible

Table 1-Sampling adequacy index and Bartlett test

KMO Index		894.0
Bartlett test	Criteria Chi-Square	756.1093
	(sig) (Significance (sig	00.00

According to (Table 1) the KMO index value of 0.894, which is close to 1 indicates that the sample size is adequate for factor analysis. In addition, the significance value of Bartlett's test is less than (0.05) confirming the suitability of factor analysis and rejecting the assumption of an identity correlation matrix.(Table 2) presents the extracted communalities of the items (questions) . Communality represents the proportion of variance in each item explained by the extracted factors . Higher communality values indicate better representation of items by the factors . Since the communality value of the tenth item is below 0.5 , this item was removed during the second stage of factor analysis .

Table 2- Extracted item subscription value

Question	Ext/Subscription	Question	Ext/Subscription	Question	Ext/Subscription
Question 1	0.657	Question 7	0.719	Question 13	0.713
Question 2	0.675	Question 8	0.768	Question 14	0.808
Question 3	0.730	Question 9	0.704	Question 15	0.666
Question 4	0.656	Question 10	0.481	Question 16	0.689
Question 5	0.704	Question 11	0.754		
Question 6	0.826	Question 12	0.811		

Based on (Table 3) it can be seen that these four factors can explain more than 71% of the variance of the items in the first stage .

Table 3- Variance explained in the first stage by four factors

Total Variance Explained									
Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	7.962	49.764	49.764	7.962	49.764	49.764	3.641	22.755	22.755
2	1.413	8.832	58.595	1.413	8.832	58.595	3.189	19.930	42.684
3	1.288	8.048	66.644	1.288	8.048	66.644	3.053	19.080	61.764
4	0.697	4.359	71.003	0.697	4.359	71.003	1.478	9.238	71.003
Extraction Method: Principal Component Analysis.									

In the second stage of factor analysis, the tenth item (question) was removed. The results are presented in (Tables 4 and 5) According to (Table 4) none of the remaining items had a commonality value below 0.5 ; therefore , no additional items were eliminated. This confirms the validity of the questionnaire. (Table 5) shows that the total explained variance (79.172) increased slightly compared to the previous stage .

Table 4- Extracted item subscription value

Question	Ext/Subscription	Question	Ext/Subscription	Question	Ext/Subscription
Question 1	0.671	Question 7	0.817	Question 13	0.713
Question 2	0.678	Question 8	0.729	Question 14	0.810
Question 3	0.740	Question 9	0.777	Question 15	0.664
Question 4	0.649	Question 10	0.705	Question 16	0.693
Question 5	0.705	Question 11	0.754		
Question 6	0.671	Question 12	0.814		

Table 5- Variance explained in the second stage by four factors

Total Variance Explained									
Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	7.527	50.180	50.180	7.527	50.180	50.180	3.341	22.272	22.272
2	1.408	9.386	59.566	1.408	9.386	59.566	3.130	20.865	43.137
3	1.286	8.576	68.143	1.286	8.576	68.143	2.972	19.815	62.952
4	0.697	4.648	72.791	0.697	4.648	72.791	1.476	9.839	72.791

In this step, the items related to each factor were identified based on the highest correlation values. As shown in Table 6, the first five questions were associated with the first factor, and similarly, the remaining questions were assigned to their corresponding factors.

Table 6- Factor Matrix

	Explained variance					Explained variance			
	Factor 1	Factor 2	Factor 3	Factor 4		Factor 1	Factor 2	Factor 3	Factor 4
Question 1	0.728	0.122	0.175	0.308	Question 9	0.556	0.185	0.598	0.056
Question 2	0.722	0.177	0.197	0.294	Question 11	0.360	0.529	0.161	0.565
Question 3	0.797	0.149	0.246	0.147	Question 12	0.263	0.260	0.085	0.819
Question 4	0.541	0.412	0.406	0.146	Question 13	-0.160	0.644	0.470	0.227
Question 5	0.608	0.469	0.253	-0.227	Question 14	0.159	0.774	0.357	0.242
Question 6	0.364	0.127	0.815	-0.057	Question 15	0.294	0.722	0.135	0.195
Question 7	0.298	0.311	0.720	0.157	Question 16	0.320	0.743	0.171	0.096
Question 8	0.148	0.300	0.802	0.151	Extraction Method: Principal Component Analysis.				
					Rotation Method: Varimax with Kaiser Normalization				

After confirming the validity, it is time to calculate the reliability. To measure the internal consistency (reliability) of the questionnaire, Cronbach's alpha coefficient is used. Cronbach's alpha is obtained based on the average covariance (or correlation) of the questions in a questionnaire. According to Table 7, which shows the Cronbach's alpha coefficient for all questions in the questionnaire, it can be concluded that the questionnaire has excellent consistency.

Table 7- Compatibility and validity of the questionnaire

Coefficient name	Amount
Cronbach's alpha coefficient	0.943

Now, looking to see if there is a significant correlation between the factors. According to Table 8, it can be seen that there is a significant correlation between all the factors, effort and performance expectations, social influence and facilitating conditions, and behavioral intention .

Table 8- Correlation between factors

Correlations						
		PE	EE	SI	FC	BI
PE	Pearson Correlation	1	0.693**	0.602**	0.597**	0.617**
	Sig. (2-tailed)		0.000	0.000	0.000	0.000
	N	113	113	113	113	113
EE	Pearson Correlation	0.693**	1	0.463**	0.634**	0.661**
	Sig. (2-tailed)	0.000		0.000	0.000	0.000
	N	113	113	113	113	113
SI	Pearson Correlation	0.602**	0.463**	1	0.652**	0.457**
	Sig. (2-tailed)	0.000	0.000		0.000	0.000
	N	113	113	113	113	113
FC	Pearson Correlation	0.597**	0.634**	0.652**	1	0.791**
	Sig. (2-tailed)	0.000	0.000	0.000		0.000
	N	113	113	113	113	113
BI	Pearson Correlation	0.617**	0.661**	0.457**	0.791**	1
	Sig. (2-tailed)	0.000	0.000	0.000	0.000	
	N	113	113	113	113	113

After evaluating the measurement model, the next step is to develop a structural model.

Table 9- Estimates of structural parameters

Result	Estimate	Respect	Hypothesis
Accept	0.617	PE → BI	H ₁
Accept	0.661	EE → BI	H ₂
Accept	0.457	SI → BI	H ₃
Accept	0.791	FC → BI	H ₄

This part presents the research questions and hypotheses related to the role of IoT , artificial intelligence, and machine learning in smart energy systems and smart grids. The results confirmed that integrating machine learning, the Internet of Things (IoT) , and artificial intelligence (AI) contributes to the digital transformation of the energy sector by improving energy efficiency, reducing losses , supporting the integration of renewable energy , and enabling smart cities and homes . However , several challenges were identified , including scalability , interoperability , data security , system reliability , regulatory considerations, and infrastructure costs . Despite these limitations, the research indicates that IoT-enabled smart energy systems can play a significant role in sustainability and environmental protection , while also supporting the development of smart grids .

7. Results and Discussion

7.1. Results Discussion

Statistical analysis showed that the collected data were suitable for factor analysis and structural equation modeling. The Kaiser-Meyer-Olkin (KMO) index registered a value of 0.894 indicating excellent sample efficiency , while the Bartlett test result was statistically significant ($p < 0.05$) confirming the existence of significant relationships between the variables. Reliability analysis yielded a Cronbach's alpha coefficient of 0.943 exceeding the generally accepted threshold of 0.70 . This result demonstrates the high quality and reliability of the questionnaire items. Factor analysis revealed that the extracted factors explain more than 72% of the total variance, indicating that the proposed model adequately reflects the relationships between the studied variables . Correlation analysis showed statistically significant positive relationships between all factors. Favorable conditions (FC) showed the strongest correlation with behavioral intention (BI) with a correlation coefficient of 0.791 . These results indicate that infrastructure readiness technical support and administrative resources play a crucial role in driving the adoption of IoT& AI& and machine learning technologies in the energy sector . The expectation of effort also showed a significant positive impact on behavioral intent (0.661) suggesting that users are more likely to adopt smart energy technologies when they find them easy to use and understand. The model's performance yielded a power factor of 0.617 demonstrating that anticipated improvements in energy efficiency and operational performance significantly influence adoption choices. Regarding social influence it registered the lowest factor (0.457) although the relationship remained statistically significant. This result suggests that external perspectives and social pressure have a less powerful impact compared to technical and organizational factors . Overall , the findings indicate that effective digital transformation in the energy sector requires not only advanced technologies but also suitable infrastructure . user support mechanisms and organizational readiness to facilitate technology adoption.

7.2. Discussion

This research presents valuable findings on accelerating the use of IoT & AI and machine learning technologies for digital transformation in the energy sector . Statistical analyses revealed that several factors play a crucial role in shaping users willingness to adopt smart energy technologies . Among these the strongest influence on behavioral willingness ($\beta = 0.791$) and ($\beta = 0.661$) indicates that the availability of infrastructure , administrative support, communication networks, trained personnel, and sufficient resources are essential for the successful implementation of smart energy and motivate users to adopt smart technologies when systems are user-friendly . Consequently , this underscores the need to develop user-friendly platforms easy to-navigate interfaces and effective training programs for both employees and customers in the energy sector . The expected performance showed a positive effect ($\beta = 0.617$) indicating that individuals and companies are motivated to adopt IoT and AI solutions when they experience tangible benefits such as energy savings, increased operational efficiency enhanced monitoring capabilities reduced maintenance costs and improved decision-making processes . While the societal impact (SI) was the lowest among the variables studied ($\beta = 0.457$) these results indicate that artificial intelligence and machine learning technologies can significantly improve smart grid operations by predicting demand detecting and maintaining faults optimizing energy consumption and integrating renewable energy sources . Despite these advantages several challenges remain, including cyber security threats, data privacy concerns device compatibility issues high implementation costs , a lack of technical expertise and limited scalability . Overcoming these challenges is crucial for enabling the widespread adoption of smart energy infrastructure

8. Conclusion

This research reveals the role of artificial intelligence the Internet of Thing and machine learning in enhancing the energy sector from a digital transformation perspective . The findings demonstrate that integrating smart sensors, smart meters, communication networks, and advanced analytical algorithms can improve energy efficiency reduce operational waste, and facilitate the development of smart grids and buildings . Enabling conditions were found to have the greatest impact on the behavioral intent to adopt smart energy technologies , followed by effort expectations, performance expectations, and social impact. These results prove that the success of digital transformation depends not only on technological innovation but also on infrastructure readiness, regulatory support, and user acceptance . They also highlight the importance of integrating smart data collection technology real-time monitoring and machine learning-based decision support systems for sustainable energy management . In practical terms , these findings can support policymakers energy providers utilities and smart grid developers in designing effective digital transformation strategies . Furthermore the success of smart energy initiatives can be enhanced through investments in communication infrastructure cyber security mechanisms employee training programs, and smart energy management platforms. Despite the positive results, some limitations should be noted. The study relied on surveys of a specific population group and a particular geographic context . Furthermore, the analysis focused primarily on factors influencing technology acceptance and did not include operational performance metrics for smart grid applications in real-world scenarios . Therefore caution should be exercised when generalizing the findings to other environments and sectors .

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