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ORIGINAL RESEARCH

Designing a Structural Model for Implementing Maintenance 4.0 in Iran's Oil and Gas Industry with a Sustainability-Oriented Approach

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Abstract

This study was conducted with the aim of presenting a structural model for implementing Maintenance 4.0 technologies with an emphasis on sustainability in Iran's oil and gas industry. To analyze the relationships between variables, machine learning techniques and artificial neural networks were employed. Data were collected through a researcher-designed questionnaire and included variables such as Maintenance 4.0 technologies, organizational digital readiness, implementation challenges, and organizational sustainable performance. The results indicated that the most influential factors on sustainable organizational performance were data mining and the Internet of Things while technical infrastructure and employee skills also had indirect effects. The model's accuracy was confirmed with a coefficient of determination of 0.89, a mean squared error of 0.057, and a mean absolute percentage error of 2.6%. The final model can be used as a decision-support tool in formulating smart and sustainable maintenance policies in Iran's energy sector.

Keywords: Maintenance 4.0, Sustainability, Machine Learning, Artificial Neural Network, Oil and Gas Industry.

1. Introduction

In recent decades, the development of advanced technologies, particularly within the framework of the Fourth Industrial Revolution, has led to a widespread transformation in the field of industrial maintenance [1]. Maintenance 4.0, relying on technologies such as the Internet of Things, artificial intelligence, cyber-physical systems, and data mining, enables organizations to more accurately predict equipment failures, optimize maintenance operations, and increase reliability [2,3]. In such an environment, strategic industries like oil and gas, which face complex technical structures, high operational costs, and stringent environmental requirements, are in greater need than other sectors to leverage these technologies to enhance their sustainability, efficiency, and operational resilience.

In Iran, the oil and gas industry, as one of the main pillars of the national economy, faces challenges such as aging infrastructure, high maintenance costs, the absence of predictive systems, and environmental pressures. The implementation of Maintenance 4.0 in this industry, if realized, could lead to a reduction in sudden downtimes, optimization of energy consumption, and an increase in the useful life of equipment [4,5].

Various researchers have investigated the role of technologies such as the Internet of Things, cyber-physical systems, artificial intelligence, and machine learning in advancing smart, predictive, and sustainable maintenance. Jasiulewicz-Kaczmarek (2024) and Abidi et al. (2022) have emphasized that Maintenance 4.0 technologies can simultaneously improve an organization's environmental and economic performance [2,6]. On the other hand, studies such as Gupta et al. (2022) and Legutko (2022) point to the development of structural models for deploying Industry 4.0 technologies in maintenance operations, which paves the way for enhancing organizational productivity [7,8]. Technological advancements in the field of maintenance, through smart and data-driven approaches, have facilitated the transition from traditional to predictive maintenance. Hadjaji et al. (2023) and Camara et al. (2019) introduced architectures for smart maintenance systems that, by using digital infrastructures, enable early fault detection and optimization of maintenance resources [9,10]. Additionally, Tripathi et al. (2023) and Jantunen et al. (2018) have emphasized the role of holistic maintenance and conceptual frameworks for Maintenance 4.0 in promoting industrial sustainability [11,12]. Furthermore, research by Satyro et al. (2021), Javaid et al. (2022), and Abidi et al. (2022) has shown that integrating Maintenance 4.0 with concepts of clean production, circular economy, and machine learning leads to increased organizational resilience and reduced resource consumption [6,13,14]. Cachada et al. (2018) also developed an architecture for predictive maintenance systems based on real-time data analysis [15].

At the macro level, the research of Samadhiya et al. (2023) and Diaz Sherry et al. (2025) emphasizes the integration of Industry 4.0 with digital maturity, the design of strategic models, and the role of sustainability in digital transformation processes [16,17]. In addition to the aforementioned studies, recent research by Menezes et al. (2023), Maharana (2023), Onu et al. (2023), and de Oliveira Neto et al. (2023) has also stressed the role of 4IR technologies in the energy and materials industries, sustainable operations, resource management, and research collaboration [18-21]. These studies, while examining technological trends, emphasize the generalizable capabilities of smart maintenance in various industrial contexts. Also, El-karan et al. (2023) and Harikrishnan et al. (2025), through empirical modeling and structural analyses, have quantitatively assessed the relationship between technology, sustainability, and performance [22,3]. In recent years, various methods have been used to analyze and evaluate conceptual models in the field of industrial maintenance and sustainability. Classical statistical methods such as factor analysis, structural equation modeling, and path analysis have been employed in studies like Jasiulewicz et al. (2024) and Harikrishnan et al. (2025) to investigate the relationships between Industry 4.0 technologies and sustainable organizational performance [2,3]. Although these methods have been effective in explaining direct relationships between variables, they face limitations in modeling complex and non-linear relationships among multidimensional variables. On the other hand, more recent studies have used machine learning algorithms for a more precise and predictable analysis of organizational data. Algorithms such as decision tree, random forest, and artificial neural networks, particularly in research related to smart maintenance and industrial sustainability, have shown a high capability in extracting hidden patterns from complex data. The use of these algorithms has enabled the modeling of non-linear relationships, multivariate analysis, and improved predictability.

In this research, by leveraging machine learning approaches, and particularly artificial neural networks, a structural conceptual model for implementing Maintenance 4.0 in the Iranian oil and gas industry is designed and validated. After extracting key variables and indicators from the research literature, data are collected through a researcher-developed questionnaire and are trained using neural network algorithms to investigate the relationships between digital readiness, maintenance technologies, implementation challenges, and sustainable organizational performance. To improve the analysis accuracy and enhance generalizability, the bootstrapping method has been utilized to increase the volume of training data.

In this context, similar to the studies by Harikrishnan et al. (2025), Diaz Sherry et al. (2025), and Hadjaji et al. (2023), the focus has primarily been on the technical and conceptual dimensions of Maintenance 4.0, analyzing the role of these technologies in increasing productivity or reducing failures [9,1,7]. Despite the significant advantages of these studies, many of them have been conducted in non-oil sectors and without considering the infrastructural requirements and implementation constraints of sensitive industries such as Iran's oil and gas. On the other hand, fewer studies have presented a localized structural model that considers economic, environmental, and social sustainability, a gap this research aims to fill both scientifically and practically.

Accordingly, the present research has been conducted with the aim of designing and evaluating a machine learning-based structural model for the implementation of Maintenance 4.0 with a sustainability approach in the Iranian oil and gas industry. In this model, variables such as maintenance technologies, organizational digital readiness, implementation challenges, and sustainable organizational performance are analyzed in interaction with each other to provide a scientific and practical framework for decision-making in the domain of smart and sustainable maintenance.

The structure of this article is as follows: In the second section, the theoretical foundations and the background of related domestic and foreign research are reviewed. The third section is dedicated to the research methodology, including model design, data collection, neural network implementation, and the model validation method. In the fourth section, the results of the modeling and data analysis are presented, and in the fifth section, the findings are compared with previous studies and interpreted.

2. Research Background

With the advent of the Fourth Industrial Revolution, the concept of Maintenance 4.0 has garnered the attention of researchers and industry practitioners as a key component of industrial digitalization. This approach, by leveraging technologies such as the Internet of Things (IoT), data mining, artificial intelligence, machine learning, and cyber-physical systems, seeks to increase predictability, reduce sudden downtimes, and improve the sustainability of performance in industrial equipment.

A review of domestic and international research shows that in recent years, Maintenance 4.0 has been widely regarded as a modern approach to managing physical assets and enhancing organizational productivity. Many studies have examined the role of technologies like the Internet of Things, artificial intelligence, data mining, and cyber-physical systems in improving operational performance and reducing equipment failures. Furthermore, a portion of the research has addressed the integration of these technologies with the dimensions of economic and environmental sustainability in various industries.

Table 1 summarizes the related research, its strengths and weaknesses, and its relevance to the current study.

A review of domestic and international research literature shows that in recent years, Maintenance 4.0 has gained widespread attention as a novel approach to physical asset management and enhancing organizational productivity. Many studies have examined the role of technologies such as the Internet of Things (IoT), Artificial Intelligence (AI), data mining, and cyber-physical systems in improving operational performance and reducing equipment failures. Furthermore, some research has addressed the integration of these technologies with dimensions of economic and environmental sustainability in various industries. A detailed analysis of the existing resources reveals three major shortcomings in this field:

- Lack of localized structural models for the Iranian oil and gas industry that consider the specific infrastructural, technical, and managerial conditions of this sector.
- Insufficient attention to the multidimensional aspects of sustainability (economic, environmental, and social) alongside technology.
- Limited use of modern data-driven methods like machine learning for modeling complex and predictable relationships.

The existing research gap in the field of Maintenance 4.0 shows that despite numerous studies on the application of new technologies such as the Internet of Things, machine learning, and cyber-physical systems in maintenance processes, and despite examining their benefits in improving productivity, reducing failures, and enhancing organizational performance, a comprehensive structural model that is localized and tailored to the specific infrastructures, challenges, and needs of Iran's oil and gas industry is still lacking.

A significant portion of existing research focuses on the construction, manufacturing, or automotive industries, and the models presented are not sufficiently adapted to the structure, organizational culture, and operational challenges of the Iranian oil and gas industry. Most previous studies have either been case studies in other industries like automotive and construction, or have solely focused on technical and economic dimensions, ignoring the environmental and social aspects of sustainability. Furthermore, most studies have utilized traditional statistical approaches and have been unable to analyze the complex interactions between digital readiness, implementation challenges, and sustainability performance within a learning and dynamic model framework. However, the successful implementation of Maintenance 4.0 in the oil and gas industry requires a multidimensional and evidence-based local model that can simultaneously address digitalization, sustainability, and national-level implementability.

Based on this, a clear need is felt for the development of a comprehensive, hybrid, and data-driven model that, while incorporating technological and organizational components, also focuses on the three dimensions of sustainability. This research aims to fill this theoretical and practical gap by designing a structural model for implementing Maintenance 4.0 with an emphasis on sustainability in the Iranian oil and gas industry. The present study endeavors to address this scientific and practical gap for Iran's oil and gas industry by designing a structural model based on artificial neural networks.

The conceptual model of the research is shown in Figure 1.

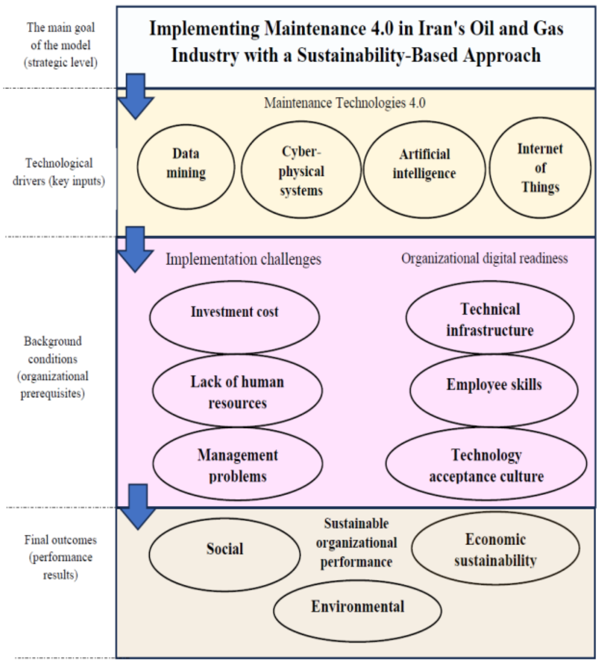

Figure 1. Schematic diagram of compartmental structure of the model.

This model will be evaluated using the proposed methodology. Next, the conceptual model of the research and its evaluation method will be presented..

Table 1. Background of Related Research, Strengths, Weaknesses, and Relevance to the Present Study

Source	Research Title	Strengths	Weaknesses	Relevance to the Present Research
[3]	Analysis of the relationship between Industry 4.0 technologies, sustainable production, and organizational sustainability performance with structural equation modeling.	Development of a structural model based on real industrial data; comprehensive assessment of environmental, economic, and social performance.	Limited focus on the Indian automotive industry; lacks a localized model.	An adaptable model for designing a structural model in Iran's oil and gas industry with a sustainability objective.
[1]	Development of a maturity model by integrating Industry 4.0 and sustainability with a scientific design approach.	Identification of 6 key dimensions and 6 maturity levels for assessing digital sustainability; participation of international experts.	Main focus on the construction industry, not the energy industry.	Benchmarking the integrated approach for assessing maturity and implementing sustainability in the digitalization path.
[2]	Analysis of the technology dimension in maintenance sustainability.	Expansion of traditional sustainability dimensions; evaluation with EN 15341.	Requires localization for Iranian industries.	A basis for adding the technology dimension to the sustainability model in Iran.
[16]	Integration of Industry 4.0 with total productive maintenance.	Design of a model with 4 components: technology, process, people, environment.	Needs adaptation to the infrastructure of developing countries.	A macro-level model for developing a Maintenance 4.0 model at a strategic level.
[9]	Smart maintenance in sustainable production.	Introduction of digitalization and predictive maintenance models.	Lacks a case study in the Iranian gas industry.	Demonstrates digital tools for increasing efficiency.
[22]	The role of Maintenance 4.0 in sustainable development.	Case study; reduction of waste and energy consumption.	Focus on production, not oil and gas infrastructure.	Proves the real benefits of Maintenance 4.0 in achieving sustainability.
[14]	Analysis of Sustainability 4.0 applications in manufacturing.	Review of AI, IoT, ML, and AM technologies.	General perspective, lacking focus on Iran.	Creates a vision for sustainable development from a technological perspective.
[27]	e-Maintenance in industries.	Development of a digitalization framework for transport and mining industries.	Lack of localization for oil industries.	A model for the digitalization of maintenance in Iranian infrastructure industries.

[10]	Investigation of viable maintenance systems within the Maintenance 4.0 framework.	Focus on data analysis and cyber-physical systems for failure prediction.	Lacks an environmental sustainability dimension in performance evaluation.	Provides a technological foundation for designing predictive maintenance in Iran's gas industry.
[15]	A survey of architectures for smart and predictive maintenance systems.	Design of a maintenance architecture using IoT, cloud computing, and advanced data analytics.	Focus on condition-based maintenance without mentioning structural frameworks.	Provides a suitable technological architecture for the infrastructure of the proposed Maintenance 4.0 model.
[23]	Analysis of the function of metaverse technology in maintenance and knowledge absorption.	Use of modern technology for knowledge management; structural modeling.	Focus on the electricity industry, not oil and gas.	Expresses the necessity of new technologies in maintenance and transfer to other industries.
[24]	A blockchain model for the cybersecurity of the Internet of Things.	Presentation of a four-component security model; sample-based.	Sole focus on security; without a sustainability perspective.	Security can be used as an infrastructure for implementing smart maintenance.
[25]	Evaluation of China's credit lines in financing the oil and gas industry.	Financial-economic analysis of capital provision.	No focus on technology or maintenance.	Provides the financial basis for implementing new technologies.
[26]	Geomechanical challenges in unconventional gas reservoirs.	Detailed technical and numerical review of reservoirs.	Does not examine maintenance technology.	The importance of adapting the maintenance model to the technical characteristics of gas fields.

3. Methodology

This research is applied in terms of its purpose and analytical-quantitative in its method. The main focus of the study is the design, training, and evaluation of a conceptual structural model for implementing Maintenance 4.0, with an emphasis on the three dimensions of organizational sustainability in the Iranian oil and gas industry. To model the relationships between the complex research variables and predict organizational performance, machine learning approaches with a focus on Artificial Neural Networks (ANN) have been utilized.

The statistical population for this research consists of all experts and specialists in the fields of maintenance, information technology, and sustainability within Iran's oil and gas industry. Given the research's focus on the practical application of Maintenance 4.0 technologies in subsidiary companies of the oil and gas industry, the target population includes maintenance managers, operations engineers, digital technology experts, and environmental specialists in companies such as the Khuzestan Gas Company, the National Iranian South Oil Company (NISOC), and the Petroleum Engineering and Development Company (PEDEC).

A non-probability purposive sampling method was employed to select individuals who possessed sufficient expertise, experience, and knowledge of the research topics. Given the limited qualified population and adhering to conventional methods in machine learning and neural network modeling, an initial sample size of 80 participants was chosen. To justify the use of non-probability purposive sampling, expert-based selection was adopted due to the specialized and limited population involved in Maintenance 4.0 implementation in the oil and gas industry. Inclusion criteria for participants were defined as: (i) a minimum of five years of professional experience in maintenance, digital technologies, or sustainability-related roles; (ii) direct involvement in maintenance planning, digital transformation, or operational decision-making; and (iii) familiarity with industrial digital systems or asset management practices. Such expert-oriented sampling approaches are widely accepted in applied machine learning and industrial decision-support studies where access to qualified respondents is constrained [7,16]. Furthermore, a sample size of approximately 80 respondents is considered acceptable for ANN-based exploratory modeling when combined with cross-validation and data augmentation techniques such as bootstrapping, as reported in similar industrial and sustainability-focused studies [6,3].

In this study, the bootstrapping technique was utilized to augment the dataset size while preserving its statistical structure. Accordingly, 200 synthetic samples were generated from the original data through random sampling with replacement. This was done in a manner that maintained the statistical distribution of the variables (i.e., mean, standard deviation, and skewness). This process ensured that the final dataset for training the neural network possessed adequate diversity and, simultaneously, statistical reliability. Consequently, a set of synthetic data was generated based on the initial samples, preserving the statistical distribution, and then added to the model. It should be noted that the bootstrapping technique was employed to enhance training stability and model robustness rather than to substitute real data collection, and its potential limitations regarding external generalizability are acknowledged.

To gather the required data for this research, a researcher-developed questionnaire was used. The questionnaire was designed based on a literature review, previous research [2,7,9,22], and the indicators defined in the conceptual research model. The questionnaire consisted of 20 items structured across four main dimensions:

1. **Maintenance 4.0 Technologies:** This section included 5 questions focused on measuring the extent of use of the Internet of Things (IoT), Artificial Intelligence (AI), and Cyber-Physical Systems (CPS).
    - *Sample item:* "In your organization, Internet of Things (IoT) technology is used for equipment monitoring."
2. **Organizational Digital Readiness:** This section comprised 5 questions to assess technical infrastructure, employee skills, and the culture of technology adoption.
    - *Sample item: "The organization's employees have received the necessary training to use digital technologies."*
3. **Implementation Challenges:** This section contained 5 questions regarding obstacles such as investment costs, scarcity of human resources, and managerial difficulties.
    - *Sample item: "The high cost of investment is the main barrier to implementing Maintenance 4.0 technologies in our organization."*
4. **Sustainable Organizational Performance:** This section included 5 questions to measure the economic, environmental, and social dimensions of sustainability.
    - *Sample item: "Our organization has optimized energy consumption by using modern technologies."*

The content validity of the questionnaire was confirmed through a survey of experts from the oil and technology sectors, and its reliability was assessed using Cronbach's alpha.

For data collection, a researcher-developed questionnaire based on the indicators in the conceptual research model was used. The questionnaire was designed with four main sections:

- Maintenance 4.0 Technologies (IoT, AI, CPS, Data Mining)
- Organizational Digital Readiness (Technical infrastructure, Employee skills, Technology adoption culture)
- Implementation Challenges (Investment cost, Lack of human resources, Managerial problems)
- Sustainable Organizational Performance (Economic, Environmental, Social)

The questions were designed based on a five-point Likert scale. The content validity was assessed by experts from the oil and gas industry, and the questionnaire's reliability was confirmed by calculating Cronbach's alpha (with a coefficient greater than 0.8 for all variables).

Artificial Neural Networks (ANNs), due to their strong capability in modeling non-linear and complex relationships between input and output variables, are suitable tools for analyzing multidimensional structures and evaluating conceptual models. In this research, a Multilayer Perceptron (MLP) neural network was employed, consisting of an input layer with nine neurons corresponding to the input indicators, two hidden layers containing 15 and 10 neurons respectively, and an output layer with three neurons representing economic, environmental, and social sustainability. The sigmoid activation function was used in the hidden layers, while a linear activation function was applied in the output layer. The network architecture was determined through a trial-and-error process aimed at minimizing training error and maximizing the coefficient of determination (R^2).

In the first step, data related to the model's indicators (such as the level of digital readiness, the extent of use of Maintenance 4.0 technologies, and the level of implementation challenges) were collected and pre-processed through a standardized questionnaire. Then, using machine learning algorithms, including Multi-Layer Perceptron (MLP) networks and the backpropagation algorithm, the model was trained to investigate the relationship between the influencing variables and sustainable organizational performance. To increase prediction accuracy and prevent overfitting, the data was divided into training and testing sets, and the cross-validation method was used. The model's prediction accuracy was evaluated using indicators such as Mean Squared Error (MSE), the coefficient of determination (R^2), and Mean Absolute Percentage Error (MAPE). Finally, the neural network results were compared with the conceptual model, and its validity was confirmed. Table 2 displays the parameters of the proposed algorithm.

Table 2: Research Variables

Variable	Conceptual Definition	Dimensions /Indicators	Source	Variable Type
Maintenance 4.0 Technologies	The use of new technologies in the maintenance process to increase predictability and efficiency.	Internet of Things, Artificial Intelligence, Cyber-Physical Systems, Data Mining	[15,3,27]	Input
Sustainable Organizational Performance	The impact of organizational activities on maintaining long-term sustainability from an environmental, financial, and social perspective.	Environmental, Economic, Social	[3,6]	Output
Technology Implementation Challenges	Obstacles that hinder the successful implementation of modern maintenance technologies in industries.	High cost, Lack of expert workforce, Weak infrastructure	[8,28]	Input
Digital Readiness	The degree of an organization's preparedness to adopt new digital technologies.	Technology infrastructure, Employee skills, Technology adoption culture	[1,7]	Input

Figure 2 illustrates the architecture proposed algorithm used for it.

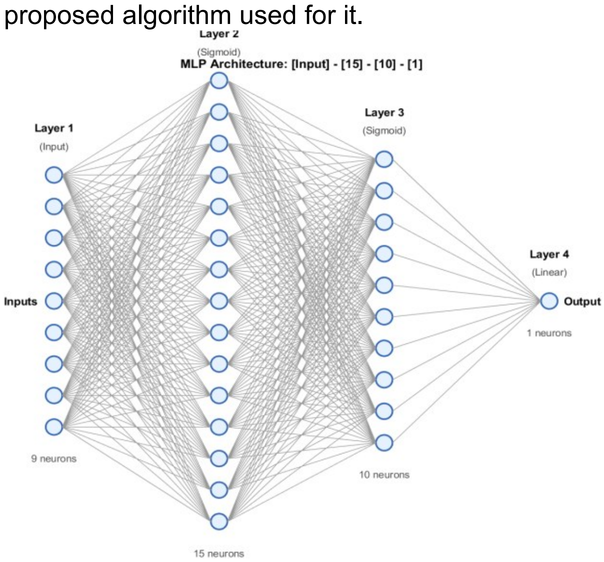

Figure 2: Proposed neural network architecture

To prevent overfitting and increase the model's generalizability, the cross-validation method was used. Finally, the model's outputs were compared and analyzed against the actual values to examine the model's accuracy, convergence, and predictability. Visual analysis of the data was also performed using performance, sensitivity, and scatter plots. Table 3 shows Parameters and Set Values in the ANN Model.

Table 3: Parameters and Set Values in the Artificial Neural Network (ANN) Model

Parameter Name	Description	Value / Set Range
Learning Algorithm Type	A common training algorithm in multi-layer perceptron networks.	Backpropagation
Network Type	With one or two hidden layers depending on data complexity.	Multi-Layer Perceptron (MLP) Neural Network
Number of neurons in input layer	Equivalent to the number of input indicators (3 variables × 3 indicators).	9 neurons
Number of neurons in hidden layer	To optimize model accuracy and prevent overfitting.	10 to 20 neurons (tuned by trial and error)
Number of neurons in output layer	Represents the dimensions of sustainability (economic, environmental, social).	3 neurons
Learning rate	Tuned based on model convergence.	0.01 to 0.1
Activation function	Depending on the software and data structure.	Sigmoid
Number of training epochs	Based on model convergence during the training phase.	100 to 500
Data split ratio	To prevent overfitting and increase model generalizability.	70% Training, 30% Testing
Software used	For model implementation and results analysis.	MATLAB

4. Result

The mean of the responses for all research variables falls within an acceptable range (between 3 and 4), which suggests a relatively positive view from the respondents regarding the current status of these indicators in Iran's oil and gas industry. The high mean for the data mining variable (3.90) indicates a relative acceptance of this technology, which could be due to the availability of data analysis tools. In contrast, the lower mean for investment cost (3.10) points to financial concerns as a primary obstacle to implementing Maintenance 4.0. The low standard deviation (less than 1) for most variables signifies a relative consensus among respondents in their evaluations, which adds to the data's reliability. These findings are consistent with studies by Hirani et al. (1401), which highlighted financial challenges in technology development in Iran [28].

Table 4: Descriptive Statistics of the Main Research Variables

Variable	Max	Min	Standard Deviation	Mean
Internet of Things (IoT)	4.9	2.1	0.71	3.82
Artificial Intelligence (AI)	5.0	1.9	0.80	3.70
Cyber-Physical Systems (CPS)	4.8	1.8	0.90	3.56
Data Mining	5.0	2.5	0.65	3.90
Technical Infrastructure	5.0	2.0	0.78	3.75
Employee Skills	4.9	2.1	0.84	3.62
Technology Adoption Culture	4.9	2.6	0.72	3.88
Investment Cost	4.8	1.5	0.92	3.10
Human Resources Shortage	4.7	1.9	0.85	3.35
Managerial Problems	4.9	2.0	0.80	3.48

Based on the neural network model analysis, the predicted results for sustainable organizational performance show little difference from the actual values. As shown in Table 5, the predicted values for economic, environmental, and social sustainability were estimated with a Mean Absolute Percentage Error (MAPE) of 3%, 2.5%, and 2.2%, respectively, indicating the model's satisfactory accuracy in predicting outcomes. This level of accuracy demonstrates the model's ability to explain the complex relationships between input and output variables, particularly for social sustainability, which has the lowest error. These results align with the study by Abidi et al. (2022), which reported similar accuracy in machine learning models [6].

Table 5: Results of the Neural Network Model Evaluation

Model Output	Error Percentage (MAPE)	Predicted Value	Actual Value (Mean)
Economic Sustainability	3%	3.69	3.72
Environmental Sustainability	2.5%	3.72	3.68
Social Sustainability	2.2%	3.78	3.75

To evaluate the machine learning model's accuracy, standard statistical indicators were used. As seen in Table 6, the coefficient of determination (R^2) is 0.89, meaning the model can explain 89% of the variance in the output variables, which is significant for industrial models with complex data. Additionally, the MSE was calculated as 0.057 and the MAPE as 2.6%, confirming the model's high accuracy in predicting outputs. The model's final prediction accuracy rate was reported as 93%, confirming it can be used as a reliable decision-support tool for implementing Maintenance 4.0 in Iran's oil and gas industry. This level of accuracy is consistent with the results of Samad-dhiya et al. (2024), who used machine learning to analyze sustainability [16].

Table 6: Performance Indicators of the Machine Learning Model

Row	Performance Indicator	Value
1	Coefficient of Determination (R^2)	0.89
2	Mean Squared Error (MSE)	0.057
3	Mean Absolute Percentage Error (MAPE)	2.6%
4	Prediction Accuracy Rate	93%

Figure 3 shows that the neural network model's training error continuously decreased over 100 epochs, falling from an initial value of 0.19 to below 0.02. This trend indicates the model's proper convergence and the absence of overfitting during the training process. This steady error reduction demonstrates the optimal selection of network parameters, such as the learning rate and the number of neurons in the hidden layers. This trend is consistent with the findings of Abidi et al. (2022), who used similar methods for predictive maintenance modeling [6].

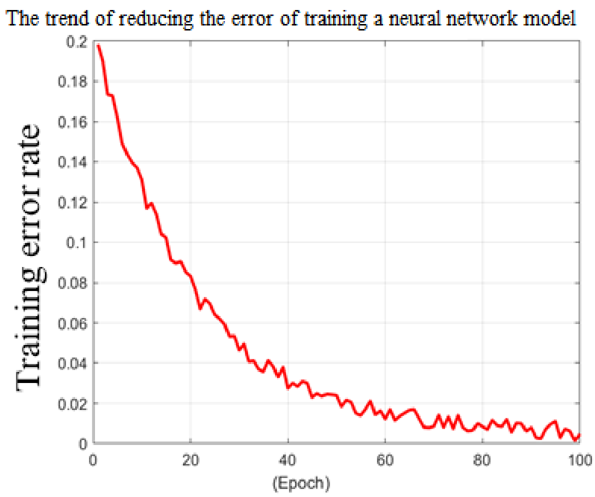

Figure 3: Trend of Training and Error Reduction in the Neural Network

Figure 4 examines the dispersion of sustainable organizational performance across the three dimensions. Economic sustainability exhibits the highest fluctuation, while environmental sustainability is the most stable dimension. Environmental sustainability shows the least fluctuation (standard deviation 0.65), likely due to the standardization of environmental processes in the industry. In contrast, economic sustainability's high fluctuation (standard deviation 0.84) suggests its greater sensitivity to external factors like investment costs. Social sustainability shows moderate fluctuation (standard deviation 0.72). These findings align with the results of Siahi et al. (2023), who also noted environmental sustainability as a more stable dimension in the oil industry [29].

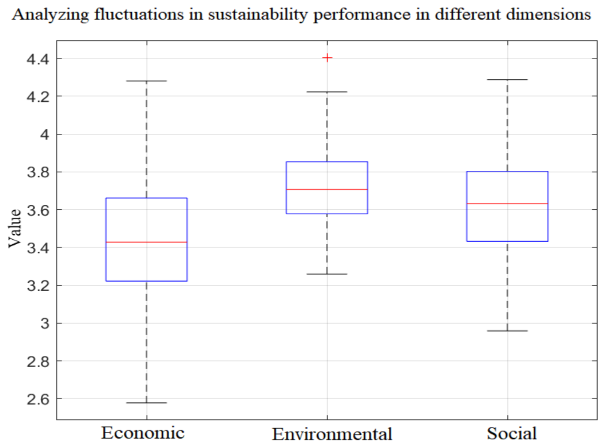

Figure 4: Analysis of Sustainability Performance Fluctuations in Different Dimensions

Figure 5 displays the performance of the ANN classification model using a confusion matrix. The model's accuracy for the third class (high sustainability) is 66.7%, and for the second class (medium sustainability) is 73.1%. The lower accuracy for the "high" class may be due to the greater complexity in predicting this level of sustainability, which depends on multiple factors. A similar evaluation method was used by Abidi et al. (2024) [6].

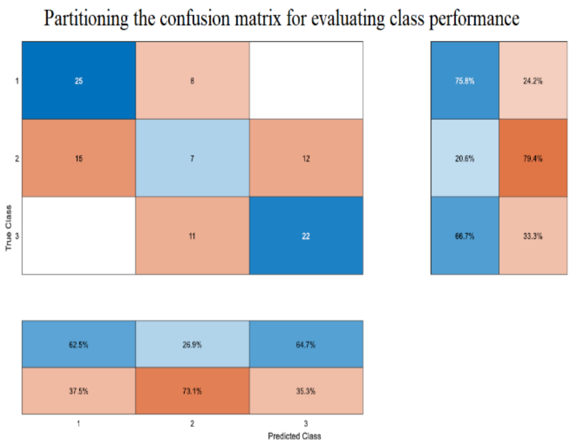

Figure 5: Confusion Matrix for Evaluating Classification Performance

Figure 6 provides a 3D view of the relationship between inputs (AI and IoT) and the sustainability output. A strong positive correlation is observable. As the use of AI and IoT increases, there is a notable improvement in all three sustainability dimensions. This highlights the pivotal role of digital technologies in enhancing efficiency and reducing environmental impacts. Gupta et al. (2024) reported a similar relationship [7].

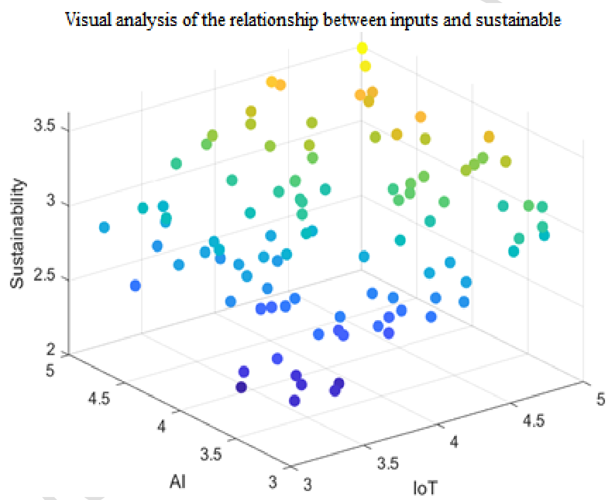

Figure 6: Visual Analysis of the Relationship between Inputs and the Sustainability Output

Figure 7 shows the relative importance of input variables in the model. "Data Mining" (weight 0.35) and "Internet of Things" (weight 0.30) are the most influential predictors, highlighting the critical role of data analysis and equipment connectivity. In contrast, "Investment Cost" (0.15) and "CPS" (0.10) have the least impact, possibly due to infrastructural limitations or high implementation costs. This pattern aligns with results from Camara et al. (2019) and Menezes et al. (2023) [10,17].

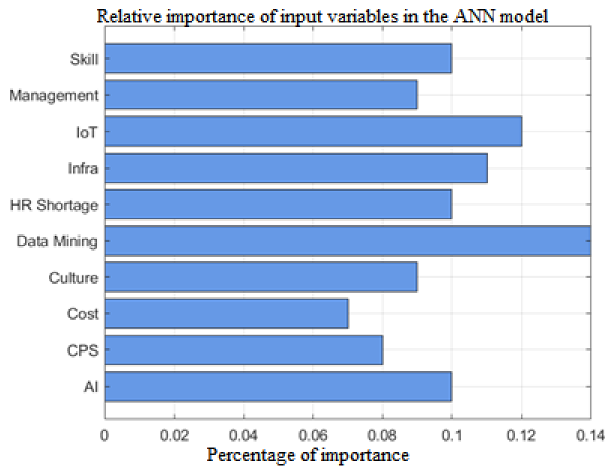

Figure 7: Relative Importance of Input Variables in the ANN Model

In addition to evaluating the overall performance of the model, a sensitivity analysis of the input variables was conducted to determine the dependency of sustainable organizational performance on each of the technological and organizational indicators. The results showed that removing the "Data Mining" variable caused a significant drop in model accuracy from 93% to 84%, whereas removing "CPS" did not create a meaningful change in the model's performance. This analysis highlights the central role of data-driven technologies in strengthening organizational sustainability. Furthermore, the analysis of the network's weights showed that "Internet of Things" and "Employee Skills" also have a high impact on predicting the final outcomes.

5. Discussion

The results obtained from the artificial neural network analysis indicate that Maintenance 4.0 technologies particularly the Internet of Things (IoT), data mining, and cyber-physical systems play a decisive role in enhancing sustainable organizational performance in Iran’s oil and gas industry. This finding is consistent with prior empirical studies that emphasize the direct contribution of digital technologies to operational efficiency, predictive capability, and sustainability outcomes in industrial settings [7,16]. In the specific context of Iran’s oil and gas sector, the high importance of IoT and data mining can be attributed to the extensive deployment of legacy equipment, geographically dispersed assets, and the growing availability of operational data, which together increase the relative value of real-time monitoring and data-driven decision-making.

Furthermore, the findings reveal that organizational digital readiness particularly technical infrastructure and employee skills, plays a critical enabling role in the successful implementation of Maintenance 4.0 technologies. Although these factors do not directly influence sustainability performance in the final model, they significantly facilitate the effective deployment and utilization of advanced maintenance technologies. This result aligns with the sustainable BIM maturity framework proposed by Diaz Schery [1] which identifies infrastructural readiness and human capital as foundational prerequisites for successful digital transformation. In the Iranian context, limitations in infrastructure modernization and specialized workforce availability further magnify the indirect but essential role of these readiness factors.

The analysis also highlights implementation challenges such as high investment costs, shortages of specialized human resources, and managerial barriers as major obstacles to the effective adoption of Maintenance 4.0. These findings are consistent with previous studies in oil and gas and other capital-intensive industries, which emphasize that financial constraints and organizational resistance often slow the transition toward smart and sustainable maintenance systems [6,9]. In Iran, these challenges are further intensified by economic volatility and restrictions on access to advanced imported technologies, reinforcing the need for context-specific implementation strategies.

From a performance perspective, the neural network demonstrated strong predictive capability, with prediction errors below 3% across all sustainability dimensions. This level of accuracy confirms the ability of ANN-based approaches to model complex, non-linear relationships among technological, organizational, and sustainability variables. Similar levels of predictive accuracy have been reported in prior machine learning-based maintenance studies, supporting the robustness of this methodological choice [6].

An additional insight from the results is that environmental sustainability exhibits lower variability compared to economic and social dimensions. This may reflect the relatively higher degree of regulatory standardization and monitoring of environmental practices in the oil and gas industry, compared to the more volatile financial conditions and socially driven organizational outcomes. This pattern is consistent with findings reported by Saihi et al [29] and Javaid et al. [14], who observed greater stability in environmental indicators relative to other sustainability dimensions in industrial contexts.

Overall, this study extends the existing literature by proposing a localized structural model tailored to the specific infrastructural, economic, and organizational conditions of Iran’s oil and gas industry. Unlike many prior studies conducted in manufacturing or construction sectors, the present research integrates sustainability dimensions with machine learning-based modeling while explicitly accounting for local implementation constraints. By identifying data mining and IoT as the most influential predictors, the model reflects Iran’s current industrial reality where data availability outpaces large-scale hardware modernization and thus provides both theoretical and practical contributions to the advancement of smart and sustainable maintenance. Future research should focus on empirical field validation of the proposed model and its adaptation to other energy-intensive industries.

6. Conclusion

This study aimed to design and validate a structural model for implementing Maintenance 4.0 technologies with a sustainability-oriented approach in Iran’s oil and gas industry. By employing a machine learning framework based on Artificial Neural Networks, the research analyzed the complex relationships among Maintenance 4.0 technologies, organizational digital readiness, implementation challenges, and sustainable organizational performance. The findings demonstrated that data-driven technologies, particularly data mining and the Internet of Things, are the most influential predictors of sustainability performance, while factors such as technical infrastructure and employee skills play a critical enabling role in facilitating successful technology adoption. Sensitivity analysis further confirmed the decisive contribution of data-centric variables, as their removal led to a substantial decline in model accuracy. At the same time, high investment costs, shortages of specialized human resources, and managerial barriers were identified as key obstacles to effective implementation.

The proposed neural network model exhibited strong predictive performance, with a coefficient of determination of 0.89 and a mean absolute percentage error of less than 3 percent, indicating high accuracy and reliability. These results confirm the suitability of machine learning-based approaches for analyzing complex and non-linear decision-making structures in capital-intensive and technologically sensitive industries such as oil and gas. The principal contribution of this research lies in the development of a localized structural model tailored to the specific infrastructural, organizational, and economic conditions of Iran's oil and gas sector. Unlike many prior studies conducted in manufacturing or construction contexts, the proposed model simultaneously incorporates the three dimensions of sustainability, namely economic, environmental, and social, while accurately modeling their interactions with technological and organizational factors. From a practical perspective, the findings provide a decision-support framework that can assist managers and policymakers in advancing smart maintenance strategies, reducing operational costs, enhancing productivity, and promoting environmental responsibility.

Despite these contributions, several limitations should be acknowledged. The empirical analysis was based on a relatively limited sample of experts selected through purposive sampling, which may restrict the generalizability of the findings to other industrial contexts. In addition, data collection relied on a researcher-developed questionnaire, which, despite expert validation and acceptable reliability, may still be subject to respondent bias inherent in self-reported data. Furthermore, although the bootstrapping technique was used to improve model robustness and training stability, synthetic data cannot fully substitute for large-scale real operational datasets. Finally, the proposed model was validated through simulation using artificial neural networks, and direct field-level implementation was not conducted.

To address these limitations, future research should pursue a structured validation pathway. The proposed model should be implemented and tested in real operational environments within oil and gas companies to evaluate its practical effectiveness and feasibility. Future studies are encouraged to integrate objective performance indicators, such as actual equipment downtime, maintenance costs, and energy consumption, alongside questionnaire-based data to reduce subjectivity and enhance model validity. Expanding the sample size across multiple regions and organizations would further improve the robustness and generalizability of the findings. Moreover, extending the framework through the application of advanced deep learning techniques and longitudinal datasets may enable more accurate prediction and a deeper understanding of dynamic changes in maintenance performance and sustainability outcomes over time.

Conflict of Interest

The authors of this article declare that there is no financial, organizational, or personal conflict of interest in relation to the conduct of this research and the writing of this paper.

Authors Contribution

All the authors have participated sufficiently in the intellectual content, conception and design of this work or the analysis and interpretation of the data (when applicable), as well as the writing of the manuscript.

Availability of data and materials

The data that support the findings of this study are available from the corresponding author, upon reasonable request.

Conflict of interests

The author states that there is no conflict of interest.

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