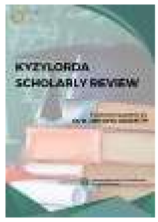
Journal of Kyzylorda Scholarly Review

P-ISSN:3006-0265 | E-ISSN:3007-4681. Published by the Open University of Kyzylorda

https://bulletin.ouk.kz/index.php/bulletin/index



THE IMPACT OF DIGITAL TWIN CAPABILITIES ON PREDICTIVE MAINTENANCE PERFORMANCE: AN ANALYTICAL STUDY

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Abstract. This research investigates how the use of digital twin capabilities will enhance the predictive maintenance performance in the Samarra Thermal Power Plant. The focus is placed upon five key dimensions of digital twin capability; that being real-time monitoring, digital simulation, fault prediction, intelligent decision-making and digital integration. Descriptive analysis was used to analyze all the relationships outlined by this study. The population for this study comprised 113 technical managers, engineers and programmers. From these, a stratified random sample of 70 respondents was chosen. Electronic questionnaires based upon previously relevant studies were distributed to collect data.
A number of statistical methods were used in the study with the help of SPSS version 24 and Microsoft Excel to analyze the information gathered from the participants. Descriptive statistics, Pearson's correlation analysis and Ordinary Least Squares (OLS) regression analysis are some examples of these statistical methods. In accordance with the findings, there is an extremely high positive correlation between Digital Twin Capability and Predictive Maintenance Performance. Additionally, it has been found that each dimension of Digital Twin Capability positively impacts Predictive Maintenance Performance; this demonstrates the capability of Digital Twins to enhance Fault Prediction Accuracy, Reduce Unplanned Downtime, Lower Maintenance Costs, Enhance Asset Reliability and Increase Equipment Lifecycle.
Recommendations made by this research are that there is a need for increased use of digital twin technologies across industrial organizations, as well as an increase in the degree of integration of these technologies into other forms of digital technology to enhance the maintenance effectiveness and reliability of operations. This research provides original data on the extent to which Digital Twin Capabilities can be used to provide improvements in Predictive Maintenance Performance within the Iraq Energy Sector.

Keywords: digital twin capabilities, predictive maintenance performance.

Introduction

Organizations with a contemporary industrial model are facing revolutionary changes due to new technological developments for the Fourth Industrial Revolution. These technological advancements have dramatically changed how organizations manage their industrial operations and equipment. As a result of increasing system complexity and increasing cost associated with unplanned downtime, organizations are looking for smarter ways to ensure equipment reliability and optimize operation performance. Therefore, predictive maintenance is now considered one of the most significant and current methods to be used in reducing unplanned downtime and improve the utilization of resources and to maintain operational continuity.

Over the last few decades there was a shift in the philosophy of maintenance, moving away from classic approaches such as repair after a failure or routine preventive maintenance towards "smart" approaches relying on data and big data analytics. Predictive maintenance today can be considered as one of the key building blocks of Smart Asset Management due to its advantages including lower operational cost, longer useful life of assets and improved operation availability. Many studies demonstrated how predictive maintenance is currently becoming a strategic approach of many industrial organizations aiming at achieving higher level of operational efficiency and organizational excellence [1], [2], [3].

Against this backdrop of an ever-evolving smart industrial world, a new exciting technological innovation is emerging as one of the top most innovative smart-industrial technologies. The term "Digital Twin" can be defined as a digital representation (model) of a physical asset; however, it does differ from simply having a computer model of a physical asset. This type of model is dynamic, which means it reflects the changing status of the physical asset. It also exists in parallel with reality, through a steady stream of information exchange between the physical asset and its digital equivalent [4].

A research conducted by Singh et al. (2023), shows that a digital twin provides an integrated digital environment allowing organizations to monitor their equipment on-line, identify potential faults, and assess the remaining life of operational elements resulting in improved predictive maintenance effectiveness and increased asset management efficiency. In addition, Yang et al. (2022), stated that the actual benefit of a digital twin was not just to represent the physical asset itself, but also to support forecasting and improve continuously through the integration of physical model, operational data and analytical intelligence.

With the expansion of Digital twin applications and artificial intelligence analysis becoming a key element for enhancing its value generation capabilities; Digital twins produce large amounts of operational data. However, to take advantage of this operational data, advanced analytical tools are required that will allow raw data to be converted into useable insights for decision making. Therefore, the importance of AI Analytics has been established as it relies on machine learning, deep learning and big data analysis in order to discover hidden patterns and predict future behaviour of industrial assets [5].

Recent studies have indicated that the application of Digital Twins integrated with AI Analytics is currently regarded as one of the largest growing research areas for Asset Management and Predictive Maintenance. The results from Zaheers (2025) study showed that when the two technologies are combined, organizations can identify potential failures and anomalies earlier than previously possible allowing them to make proactive decisions on how to address the issues via their maintenance and risk management strategies. Similarly, Prabu et al. (2025) found that when AI was integrated with Digital Twins it improved the accuracy of fault predictions, reduced unplanned downtime and increased overall operational efficiencies within Smart Manufacturing Environments.

Although there has been significant advancement in using Digital Twin and Artificial Intelligence (AI) for their respective uses, many prior research studies have mainly examined the technological and engineering aspects of developing digital models as well as enhancing the accuracy of fault prediction algorithm. An example is that study by Abdullahi et al. (2024), which developed a Distributed Digital Twin Framework for supporting Predictive Maintenance in Industrial Systems; an example of another study is that conducted by Mutlu and Kaewunruen (2026) for assessing the application of Digital Twins and Artificial Intelligence for enhancing railway infrastructure maintenance. While both of these studies were important, neither of them provide adequate information regarding how the ability of Digital Twin can be translated into tangible organizational-level strategic results [6].

Moreover, there is an obvious need to study the relations between digital twin capabilities and predictive maintenance performance as well as between digital twin capabilities and operational excellence in the management and organisation literature. Moreover, so far, there has been too little attention given to the role of Artificial Intelligence (AI) Analytics in explaining these relationships. Although increasing amounts of empirical evidence demonstrate that AI is a crucial link between enhanced digital capabilities and successful operational results, this has recently been supported by calls from other studies for the establishment of more complete research frameworks that will integrate digital capabilities, smart analytical tools and organisational performance results into a single theoretical framework [7], [8].

Building upon this identified knowledge gap, the objective of the current research is to investigate the strategic contribution of Digital Twin (DT) capabilities for Predictive Maintenance (PdM) performance as well as Operational Excellence, while simultaneously investigating whether Artificial Intelligence (AI) Analytics acts as an intermediary factor within these DT capability – PdM/Operational Excellence relationships. A major advantage of this approach lies in the fact that it provides a combined view of both perspectives i.e. Digital Capabilities Perspective and Operations and Asset Management Perspective; therefore, enabling industrial organizations to have a better comprehension of how they can strategically derive long-term value from their investments in DTs and AI Technologies.

Methods

1. Research Philosophy and Approach (Research Philosophy and Approach)

The present research is based on Positivist Philosophy, which assumes that organisational and technological phenomena can be studied objectively through observation, measurement and statistical analysis. This philosophy is suitable for studying the causal relationships between digital twin capabilities and predictive maintenance performance, and for testing hypotheses derived from the existing literature. The research adopts a deductive approach, whereby a theoretical framework and research hypotheses are developed based on previous literature relating to digital twins and predictive maintenance, and these hypotheses are then tested empirically using quantitative data.

2. Research Problem

Despite the rapid development of digital twin applications within industrial environments, the current literature focuses largely on the technical aspects associated with building digital models and predictive algorithms, whilst understanding of the impact of digital twin capabilities on improving predictive maintenance performance remains limited, particularly from a managerial and organisational perspective. Hence, the research problem lies in attempting to answer the following main question:

"To what extent do digital twin capabilities contribute to improving predictive maintenance performance in industrial organisations?"

a. What is the level of digital twin capabilities in the industrial organisations under study?
b. What is the level of predictive maintenance performance in the industrial organisations under study?
c. Is there a significant correlation between digital twin capabilities and predictive maintenance performance?
d. Do digital twin capabilities have a significant impact on predictive maintenance performance?
e. Which dimensions of digital twin capabilities have the greatest impact on predictive maintenance performance?

3. Research Objectives

a. To determine the level of implementation of digital twin capabilities in the industrial organisations under study.

b. To measure the level of predictive maintenance performance.
c. To analyse the relationship between digital twin capabilities and predictive maintenance performance.
d. To test the direct impact of digital twin capabilities on predictive maintenance performance.
e. To provide a scientific framework to help the industrial organisations under study improve predictive maintenance performance through the development of digital twin capabilities.

4. Conceptual Framework

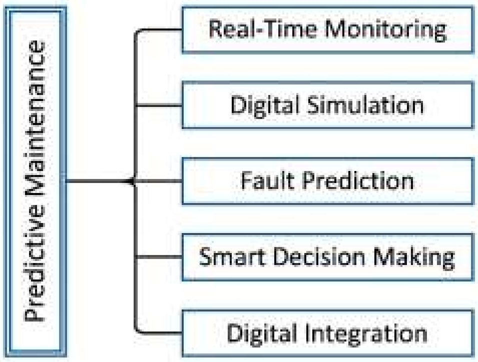

Figure 1. Research Hypothesis Diagram

5**. Research Hypotheses**

H1 Main Hypothesis: Digital twin capabilities have a positive and significant effect on predictive maintenance performance.

A number of sub-hypotheses stem from the main hypothesis, including:

H11 – Real-time monitoring has a positive effect on predictive maintenance performance.
H1 – Digital simulation has a positive effect on predictive maintenance performance.
H13 – The ability to predict faults has a positive effect on predictive maintenance performance.
H14 – The ability to make intelligent decisions has a positive effect on predictive maintenance performance.
H15 – Digital integration has a positive effect on predictive maintenance performance.

6**. Research Field, Population and Sample**

The research field was the Samarra Thermal Power Station, an electricity generation company, and the study population consisted of a number of technical managers and software engineers totalling 113. A stratified random sample of 70 individuals was selected. An electronic questionnaire was adopted as the primary tool for data collection.

Thirdly: Literature Review

1. The Concept of the Digital Twin

The Digital Twin is one of the most prominent outcomes of digital transformation and the Fourth Industrial Revolution. It refers to a dynamic digital representation of physical assets or systems that relies on the continuous integration of real-world data and virtual models for monitoring, simulation, analysis, prediction and decision support [9], [10], [11]. The concept has evolved from a mere virtual model of a physical asset to an integrated cyber- -physical system that utilises Internet of Things (IoT), big data, artificial intelligence and cloud computing technologies to establish a continuous connection between the physical and digital worlds, thereby enabling the real-time updating of the digital model and the analysis of assets' operational performance throughout their lifecycle [10], [12], [13].

Recent literature agrees that the intrinsic value of the digital twin lies not only in representing the physical asset, but also in its ability to provide real-time visibility into operational status, simulate future scenarios, predict potential failures, and improve operational and strategic decisions [9], [11], [14]. Applied studies in the manufacturing, energy, infrastructure and transport sectors have also demonstrated that digital twins contribute to improving asset reliability, reducing unplanned downtime, enhancing the efficiency of predictive maintenance, and promoting sustainable operational performance [12], [15], [16], [17].

Accordingly, the digital twin can be viewed as an intelligent digital platform that combines a virtual representation of assets with a continuous flow of data and advanced analytics, enabling organisations to improve asset management, enhance predictive maintenance, and achieve higher levels of efficiency and operational excellence [10], [11], [12].

1. Digital Twin Capabilities

Digital Twin Abilities are now at the centre of much research on Smart Industry and Digital Transformation because they enable organizations to use data from their operations for Predictive Insights which can be used for Strategic Decision Making to improve Operational Performance and Competitiveness. While the initial digital twin was a Virtual Representation of Physical Assets; Recent Developments with IoT, AI, Cloud Computing and Big Data Technologies have enabled Digital Twins to be transformed into Integrated Platforms capable of providing a wide variety of functionalities that go beyond what is traditionally provided by Monitoring and Simulation to provide Prediction, Optimization and Intelligent Decision-Making [10].

Recent studies have shown that digital twin capabilities can be considered as the functional and analytical potential of digital twin systems due to the permanent integration of both the physical world and the virtual world, which allows for the real time tracking of assets; analyzing their behavior while operating; predict possible failures; and improve decision making process accuracy and efficiency. Ismail et al. (2026) suggest that the most valuable part of the digital twin is not simply creating a virtual representation of a physical asset, but in its dynamic capabilities to continually learn from its operation; adapt to operational changes; and make accurate predictions that will allow for smart maintenance and effective asset management [11].

Real-time monitoring capability is another of the primary capabilities of a Digital Twin; in this way, it is possible to collect and analyze sensor and IoT data continuously, to get a complete and accurate image of the operative conditions of all of the system's components. Several studies have demonstrated how the real-time monitoring capability improves the overall situation awareness of an industrial plant (it reduces the detection time of anomalies) and therefore increases its reliability and the effectiveness of maintenance activities [14].

Simulation Capability is a primary characteristic of the Digital Twin that enables organizations to analyze the effects of possible operating modes or make choices regarding which solutions may be implemented in an actual environment prior to doing so. Simulation capability also provides opportunities to investigate how different operating conditions affect equipment behavior; assess the probability of failures occurring; estimate potential results and ultimately reduce organizational risk as well as improve the decision making processes (both technically and managerially) [13].

Predictive Capability is an example of a strategic dimension of Digital Twins and enables the use of the integration of both historical and real-time data with the application of artificial intelligence algorithms along with physical models in order to be able to forecast future states of the assets and to determine the probability of failure prior to occurrence. Zhong et al. (2023), through a study, have shown that the digital twin overcomes some of the limitations of traditional predictive maintenance by using improved forecasting accuracy; increased reliability of predictive models; and increased accuracy of remaining operational life estimates for equipment [10].

Intelligent Decision-Making Capability (IDMC) represents a leading-edge advanced capability for digital twins; by enabling the integration of artificial intelligence (AI), and machine learning (ML) based analytical functionality into the digital twin, IDMC enables proactive decision support related to optimal maintenance methods, appropriate resource allocations and the scheduling of operations in an efficient manner. Research indicates that IDMC can reduce uncertainty in decision-making, improve the speed with which responses are made to operational events and enhance the overall efficacy of managerial decision-making [18].

Integration capability is another core requirement for the success of digital twins. Digital twins are not independent entities, they integrate with many other systems including IoT devices, ERP systems, cloud-based computing services and AI/ML based services. When all these various systems are integrated together, this creates a digital ecosystem that can facilitate real-time communication across all the systems involved and enables continuous prediction of future failures and ongoing improvements to overall system performance [12].

From the perspective of Dynamic Capabilities Theory, digital twin capabilities can be viewed as a strategic resource that enables an organisation to sense and adapt to environmental changes and continuously reconfigure its resources to achieve operational excellence. The importance of the digital twin is not limited to simply possessing the technology itself, but depends on the organisation's ability to utilise this technology and transform it into operational knowledge and strategic value that supports innovation and performance improvement. Recent studies have confirmed that organisations with high levels of digital twin capabilities achieve better levels of operational reliability, efficiency and productivity compared to organisations that rely on traditional maintenance methods [15].

Based on the above, the capabilities of the digital twin can be defined procedurally in this study as: " the set of technical and analytical capabilities provided by digital twin systems to an organisation through real-time monitoring, digital simulation, fault prediction, intelligent decision-making, and integration with other digital technologies, thereby contributing to the improvement of predictive maintenance performance and the enhancement of operational excellence".

1. Predictive Maintenance (Predictive Maintenance)

Predictive maintenance is one of the most advanced maintenance strategies in smart industrial environments, as it relies on continuously monitoring the actual condition of equipment and analysing operational data with the aim of predicting potential failures before they occur and taking appropriate action at the optimal time. This strategy emerged in response to the limitations associated with traditional maintenance methods, whether corrective maintenance carried out after a failure has occurred or preventive maintenance based on fixed schedules that may not reflect the true condition of the equipment [10], [11], [13].

The literature indicates that predictive maintenance relies on data derived from sensors and monitoring systems, as well as advanced data analytics, to detect early signs of deterioration and predict future equipment conditions, thereby enabling maintenance activities to be carried out before an actual failure occurs. This approach helps to reduce unplanned downtime, lower maintenance costs, improve asset reliability and extend their operational life, as well as enhance the efficiency of operational resource utilisation [10], [16], [19], [20]. The rapid development of Internet of Things (IoT) technologies, artificial intelligence (AI), machine learning and big data analytics has enhanced the effectiveness of predictive maintenance, as organisations have become able to collect and analyse vast amounts of operational data in real time to detect abnormal patterns and predict future failures with a high degree of accuracy. Recent studies confirm that integrating artificial intelligence technologies with predictive maintenance systems helps to improve the quality of predictions, estimate the remaining useful life of equipment, and support proactive decisions regarding asset management [18], [19], [20], [21].

In recent years, predictive maintenance has become increasingly associated with digital twin applications, as this technology has provided an integrated digital environment that allows for real-time monitoring of assets, simulation of their operational behaviour, and prediction of potential failures with greater accuracy compared to traditional methods. Recent reviews have highlighted that the digital twin has become a key enabler of predictive maintenance by integrating operational data, physical models and intelligent analytics within a single platform that supports diagnosis, prediction and decision-making [9], [10], [11]. Furthermore, applied studies in the manufacturing, energy, transport and infrastructure sectors have shown that the adoption of predictive maintenance contributes to reducing unplanned failure rates, improving operational readiness, enhancing performance efficiency and promoting the economic sustainability of assets. Applications of digital twins in renewable energy systems, smart grids and manufacturing industries have demonstrated a clear ability to improve equipment reliability, reduce operating and maintenance costs, and achieve higher levels of operational efficiency [12], [15], [17], [22].

Accordingly, predictive maintenance can be defined as a proactive approach to asset management that relies on the collection and analysis of operational data and the use of analytical models and artificial intelligence to predict potential failures and determine the optimal timing for maintenance activities, thereby contributing to improved asset reliability, reduced unplanned downtime and enhanced sustainable operational performance [10], [11], [12].

1. Predictive Maintenance Performance

Predictive Maintenance Performance is one of the key indicators that reflects the extent to which organisations succeed in utilising digital technologies and operational data to improve asset reliability and enhance the efficiency of maintenance operations. Whilst predictive maintenance as a strategy focuses on predicting failures before they occur, predictive maintenance performance reflects the operational and organisational outcomes achieved through the implementation of this strategy, such as improved failure prediction accuracy, reduced unplanned downtime, lower maintenance costs, increasing equipment availability, and extending the operational life of assets [9], [10], [11].

Literature suggests that evaluating performance of predictive maintenance has become an important aspect in evaluating success of smart maintenance and asset management initiatives and this is due to its direct relationship with operational efficiency and levels of reliability. Literature also indicates that while predictive maintenance should provide ability to forecast failure events it will not be completely effective until it contributes to reducing unplanned down-time and improvements in resource utilization and delivering sustainable value for organisations both operationally and financially [16], [19], [22].

Failure Prediction Accuracy is considered by many as a leading indicator when assessing predictive maintenance performance due to its reflection on how well an analytical model or intelligent algorithm will be able to recognize the indications of wear and tear of a piece of equipment so that you can predict what condition that same piece of equipment will be in at some time in the future prior to an actual failure occurring. Studies show that high levels of prediction accuracy contribute to the improvement of your maintenance planning; to the reduction of operational risk and to the optimal use of both technical and monetary resources. [18], [21].

Furthermore, the decrease in unplanned downtime is one of the most critical measures for the performance of predictive maintenance due to lost production time and money caused by unexpected breakdowns. Several researchers have demonstrated that through the application of predictive maintenance with support from smart analytics and digital twin, there has been an improvement in decreasing the rate of unplanned downtimes and improving continuous operations, which results in high levels of available equipment [9], [10], [17].

The second measure that is very important is the reduction in maintenance cost. Predictive maintenance enables to perform maintenance works at the right moment and therefore avoid to maintain according to a calendar schedule or intervene only after a failure.

Research has proven that using this method will allow the best use of resources, a reduction in costs for emergency repairs and better management of maintenance expenses [11], [12], [15].

The quality of the performance in predictive maintenance has a connection with improvement of the useful residual lifetime of equipment and betterment of equipment reliability as well, since it enables the use of predictive models and digital twins to monitor the rate of degradation for many of its components and predict their remaining operative lifetime; thus enabling more precise decision-making on the timing of replacements, repairs and preventive maintenance. Research indicates that improvements in these areas will contribute to improved productivities, better operational efficiencies and longer term sustainable operation [10], [11], [19].

In recent years, the digital twin has become one of the most significant factors influencing predictive maintenance performance, as it provides an integrated digital environment that allows for real-time monitoring of assets, analysis of operational data, simulation of future scenarios, and more accurate fault prediction. Recent systematic reviews have confirmed that organisations relying on digital twin and artificial intelligence technologies achieve higher levels of predictive maintenance performance compared to those relying on traditional methods, due to improvements in data quality, fault detection speed, and the accuracy of operational decisions [9], [10], [11].

Based on the above, predictive maintenance performance in this study can be defined as: "the level of operational outcomes achieved through the implementation of predictive maintenance, reflected in the accuracy of fault prediction, the reduction of unplanned downtime, the reduction of maintenance costs, the improvement of asset reliability, and the extension of equipment service life, thereby contributing to enhanced operational efficiency and the realisation of sustainable value for the organisation".

Fourth. Research Methodology and Variables

1. Research Methodology and Procedures

In the context of analytical field research, the researcher adopted a number of methods and procedures appropriate to this context, adopting a descriptive-analytical approach to conduct the research and achieve its practical objectives, A field survey was conducted using a questionnaire prepared by the researcher for the purpose of data collection. Based on this data, descriptive and inferential analysis was carried out using a range of mathematical and statistical methods, such as the arithmetic mean, standard deviation, correlation coefficient, and the ordinary least squares (OLS) regression model (OLS) using both the statistical software (SPSS Ver.24) and the Excel spreadsheet programme, in order to extract the results, discuss them and evaluate the hypotheses.

2. Measurement of Variables

The study included two main variables: (digital twin capabilities and predictive maintenance performance), which were measured using a questionnaire prepared by the researcher. The questionnaire comprised two axes: the first axis measured the independent variable (digital twin capabilities) through 25 items divided into five dimensions (a. real-time monitoring, b. digital simulation, c. fault prediction, d. Intelligent decision-making, e. Digital integration), with five statements per dimension, whilst the second axis was dedicated to measuring the dependent variable (predictive maintenance performance) through 10 statements. These variables and their representative statements were coded as shown in Table (1), The researcher employed a five-point Likert scale to quantify the sample participants' responses, assigning a value of (1) to the response 'Strongly disagree', (2) to 'Disagree', (3) to 'Neutral', (4) to 'Agree', and finally, the response 'strongly agree' was assigned a value of 5.

Table 1. Coding of research variables and their corresponding statements

Type of Variables	Variables and Dimensions	Code	Number	Sequence
Independent	A. Real-time Monitoring	XX1	5	X1-X5
	B. Digital Simulation	XX2	5	X6-X10
	C. Failure Prediction	XX3	5	X11-X15
	D. Intelligent Decision Making	XX4	5	X16-X20
	E. Digital Integration	XX5	5	X21-X25
	Digital Twin Capabilities	X	25	X1-X25
Dependent	Predictive Maintenance Performance	Y	10	Y1-Y10

3. Testing the research instrument

The validity of the questionnaire was tested using internal consistency, calculated as the square root of the Cronbach's alpha coefficient; see the table (2), it can be seen that the reliability coefficients are very high, indicating the validity of the questionnaire; in other words, the statements in the questionnaire accurately reflect the variables being measured. Meanwhile, the stability of the questionnaire was tested using Cronbach's alpha, based on a maximum threshold value of 0.70, as this coefficient verifies that if the questionnaire is redistributed to the same individuals under similar conditions, similar responses will be obtained. Furthermore, Table 2 shows that the calculated values for Cronbach's alpha are high and exceed the assumed threshold, indicating the stability and consistency of the questionnaire. Consequently, these results support the reliability of the data collected via this questionnaire and its validity for subsequent statistical analysis in the research.

Table 2. Validity and Reliability of the Questionnaire

Variables and Dimensions	Code	Validity Coefficient	Cronbach's Alpha Coefficient	Number of Items
Digital Twin Capabilities	X	0.919	0.845	24
Predictive Maintenance Performance	Y	0.856	0.733	10

Results and Discussion

Description of the questionnaire items

The study, based on its two variables (digital twin capabilities and predictive maintenance performance), comprised 35 items, divided into 25 items for the variable 'digital twin capabilities' and 10 items for the variable 'predictive maintenance performance'. The trends in the sample participants' responses to these items were described using a number of statistical methods, such as the mean and standard deviation, as shown in Table (3).

Table 3. Description of response patterns among sample participants to statements regarding twins' digital capabilities and predictive maintenance performance

Dimension	Code	Statements	Mean	Standard Deviation	Relative Importance	Coefficient of Variation	Rank
		Statements of the digital twin capabilities variable					
Real-time Monitoring	X1	The digital twin system provides continuous monitoring of the operational status of the equipment.	3.96	0.842	79.1%	21.3%	4
	X2	The operational data of the assets is updated in real-time through the digital twin.	4.19	0.921	83.7%	22.0%	2
	X3	The digital twin contributes to improving the speed of response to operational problems through immediate monitoring.	4.13	0.992	82.6%	24.0%	3
	X4	The digital twin contributes to improving the speed of response to operational problems through	4.27	0.977	85.4%	22.9%	1

Dimension	Code	Statements	Mean	Standard Deviation	Relative Importance	Coefficient of Variation	Rank
		immediate monitoring.					
	X5	The digital twin helps in detecting operational deviations as soon as they occur.	3.94	0.991	78.9%	25.1%	5
Digital Simulation	X6	The digital twin enables the organization to test operational scenarios before actually implementing them.	4.13	0.931	82.6%	22.6%	3
	X7	The digital twin helps in evaluating the outcomes of potential operational decisions in advance.	4.21	1.006	84.3%	23.9%	2
	X8	Digital simulation models provide a better understanding of equipment behavior under different operating conditions.	3.77	1.024	75.4%	27.1%	4
	X9	The digital twin helps in analyzing the risks associated with potential failures.	4.33	0.959	86.6%	22.2%	1
	X10	Digital simulation contributes to improving the planning of maintenance operations.	3.71	0.935	74.3%	25.2%	5
Failure Prediction	X11	The digital twin enables the organization to predict potential failures before they occur.	4.39	0.967	87.7%	22.1%	1
	X12	The digital twin provides accurate estimates of the remaining	3.94	1.048	78.9%	26.6%	4

Dimension	Code	Statements	Mean	Standard Deviation	Relative Importance	Coefficient of Variation	Rank
		operational life of the equipment.					
	X13	The digital twin helps in identifying the equipment components most prone to failure.	3.74	0.958	74.9%	25.6%	5
	X14	The digital twin enhances the organization's ability for proactive maintenance planning.	4.34	0.946	86.9%	21.8%	2
	X15	The digital twin contributes to reducing sudden failure cases through early prediction.	4.27	0.931	85.4%	21.8%	3
Intelligent Decision Making	X16	The digital twin provides accurate information that supports maintenance decision-making.	3.67	1.100	73.4%	30.0%	5
	X17	The digital twin helps in selecting the most efficient operational alternatives.	4.14	0.937	82.9%	22.6%	1
	X18	The digital twin enhances the speed of decision-making related to maintenance and asset management.	4.04	1.109	80.9%	27.4%	3
	X19	The digital twin supports proactive decision-making rather than reactive decisions.	3.87	1.048	77.4%	27.1%	4
	X20	The digital twin contributes to improving the quality of operational decisions within the organization.	4.11	1.043	82.3%	25.4%	2
Digital Integration	X21	The digital twin integrates effectively with the	4.14	0.967	82.9%	23.4%	1

Dimension	Code	Statements	Mean	Standard Deviation	Relative Importance	Coefficient of Variation	Rank
		Internet of Things systems used in the organization.					
	X22	The digital twin allows seamless data exchange between different operational systems.	3.74	0.973	74.9%	26.0%	5
	X23	The digital twin integrates with maintenance and asset management systems in the organization.	3.76	1.013	75.1%	27.0%	3
	X24	The digital twin supports linking between different data sources in the work environment.	3.76	0.999	75.1%	26.6%	4
	X25	Digital integration contributes to improving the flow of information necessary for decision-making.	4.11	0.772	82.3%	18.8%	2
		Statements of the predictive maintenance performance variable					
	Y1	Predictive maintenance systems in the organization are able to predict potential failures with a high degree of accuracy before they occur.	3.97	0.932	79.4%	23.5%	5
	Y2	Predictive maintenance results provide reliable information that supports advance planning to deal with potential failures.	3.89	1.015	77.7%	26.1%	8
	Y3	Predictive maintenance has contributed to	3.81	0.967	76.3%	25.4%	10

Dimension	Code	Statements	Mean	Standard Deviation	Relative Importance	Coefficient of Variation	Rank
		reducing the number of unplanned operational downtimes for equipment.					
	Y4	Predictive maintenance helps maintain the continuity of operational processes and reduce sudden interruptions.	4.10	0.950	82.0%	23.2%	2
	Y5	The application of predictive maintenance has contributed to reducing the costs of emergency equipment repairs.	3.90	0.919	78.0%	23.6%	7
	Y6	Predictive maintenance has helped the organization improve the efficiency of spending allocated to maintenance activities.	3.99	0.807	79.7%	20.3%	4
	Y7	Predictive maintenance has contributed to improving the reliability of equipment and operational assets.	4.11	0.971	82.3%	23.6%	1
	Y8	Predictive maintenance has helped reduce the rates of recurring failures for operational assets.	3.89	0.860	77.7%	22.1%	9
	Y9	Predictive maintenance has contributed to extending the operational life of key equipment and assets.	4.10	0.871	82.0%	21.2%	3

Dimension	Code	Statements	Mean	Standard Deviation	Relative Importance	Coefficient of Variation	Rank
	Y10	Predictive maintenance has helped maintain equipment efficiency for longer operational periods.	3.91	0.897	78.3%	22.9%	6

Table (3) shows that responses tend towards high agreement for statements (X1–X25) regarding the variable 'twin digital capabilities', as perceived by the sample participants at the Samarra Thermal Power Station, an electricity generation company. This is indicated by the high mean value, which exceeded the hypothesised value of 3 for all statements. This is further confirmed by the high relative importance scores for these statements. It is also noted that statement (X4) recorded the highest level of agreement within the 'real-time monitoring' dimension, with a mean of 4.27, whilst statement (X5) recorded the lowest level of agreement, with a mean of 3.94. As for the 'Digital Simulation' dimension, statement (X9) recorded the highest level of agreement with a mean of (4.3), whilst statement (X10) recorded the lowest level of agreement with a mean of (3.71), According to the 'Fault Prediction' dimension, statement No. (X11) recorded the highest level of agreement with a mean of (4.39), whilst statement No. (X13) recorded the lowest level of agreement with a mean of (3.74), Furthermore, according to the 'Smart Decision-Making' dimension, statement (X17) recorded the highest level of agreement with a mean of (4.14), whilst statement (X16) recorded the lowest level of agreement with a mean of (3.67), Finally, according to the 'Digital Integration' dimension, statement (X21) recorded the highest level of agreement with a mean of (4.14), whilst statement (X22) recorded the lowest level of agreement with a mean of (3.74). As can also be seen from Table (3), there is a trend towards high agreement for statements (Y1–Y10) in the predictive maintenance performance variable, as perceived by staff at the Samarra Thermal Power Station, as indicated by the high mean values exceeding the assumed value of (3) for all statements. This is further confirmed by the high relative importance scores for these statements. It is also noted that statement (Y7) recorded the highest level of agreement within the predictive maintenance performance variable, with a mean of (4.11), whilst statement (Y3) recorded the lowest level of agreement with a mean of (3.81), The low standard deviation and the coefficient of variation being less than 50% indicate consistency and lack of dispersion in the sample participants' responses, which reinforces the reliability of the mean values in representing the entire sample.

2. Description of variables

Table (4) presents the descriptive analysis of the research variables (digital twin capabilities, predictive maintenance performance) in all their dimensions. This analysis was conducted using a number of statistical methods, such as the mean, standard deviation, and minimum and maximum values.

Table 4. Description of research variables

Variables and Dimensions	Code	Mean	Standard Deviation	Minimum Value	Maximum Value	Relative Importance	Coefficient of Variation	Rank	Skewness
A. Real-time Monitoring	XX1	4.097	0.516	1.80	5.00	81.9%	12.6%	2	-0.324
B. Digital Simulation	XX2	4.031	0.611	1.80	5.00	80.6%	15.1%	3	-0.103

C. Failure Prediction	XX3	4.137	0.698	1.80	5.00	82.7%	16.9%	1	-0.384
D. Intelligent Decision Making	XX4	3.969	0.720	1.80	5.00	79.4%	18.1%	4	-0.414
E. Digital Integration	XX5	3.903	0.686	1.80	5.00	78.1%	17.6%	5	-0.553
Digital Twin Capabilities	X	4.027	0.462	1.80	4.84	80.5%	11.5%	-	-0.746
Predictive Maintenance Performance	Y	3.967	0.499	1.80	4.70	79.3%	12.6%	-	-0.887

It can be seen from Table (4) that there is a high and strong level of agreement regarding the availability of the digital twin capabilities variable across its five dimensions (a. real-time monitoring, b. digital simulation, c. fault prediction, d. intelligent decision-making, e. digital integration), as perceived by the sample members at the Samarra Thermal Power Station. This is confirmed by the fact that the calculated mean value exceeds its hypothetical value of (3), as well as the high relative importance value, as the digital twin capabilities variable recorded an availability level with a mean of (4.027) and a relative importance of (80.5%). As for the dimensions, it is noted that the 'fault prediction' dimension recorded the highest availability level, with a mean of (4.137), followed by the 'real-time monitoring' dimension with a mean of 4.097, then the 'digital simulation' dimension with a mean of 4.031, followed by the 'intelligent decision-making' dimension with a mean of 3.969, and finally (Digital Integration) with an arithmetic mean of (3.903). It can also be seen from Table 4 that there is a high and strong consensus regarding the availability of the predictive maintenance performance variable, as perceived by the sample members at the Samarra Thermal Power Station, This is confirmed by the calculated mean exceeding its hypothetical value of (3), as well as the high relative importance value, as the predictive maintenance performance variable recorded an availability level with a mean of (3.967) and a relative importance of (79.3%), whilst the low value of the standard deviation and the low value of the coefficient of variation, which is below the assumed value of 50%, indicate that there is consistency and no dispersion in the sample participants' responses, thereby reinforcing the reliability of the arithmetic mean in representing the total sample.

3. Test of normality

The researcher tested the normal distribution of the data using the skewness coefficient, as this coefficient is used to verify the normality of the data, which is a key condition for using parametric statistical methods in testing research hypotheses, The value of the skewness coefficient is judged to be close to a normal distribution and to satisfy the condition of normality if it falls within the range of +1 to -1. Referring to Table 4 above, it can be seen that the calculated values for all variables and dimensions fall within the specified ranges, meaning that the data are normally distributed and satisfy the condition of normality. This enables the researcher to use parametric statistical methods to test the hypotheses later.

4. Testing the Relationship

The researcher tested the relationship between the research variables (digital twin capabilities and predictive maintenance performance) using Pearson's correlation coefficient. This coefficient is used to determine the significance, strength and direction of the relationship between these variables; a statistical significance level of 5% or less for this coefficient indicates the presence of a significant relationship between the variables, whereas if the significance level is greater than 5%, this negates the existence of a significant relationship. The value of the correlation coefficient also indicates the strength of the relationship, ranging between +1 and -1; the closer the coefficient's value is to exactly one (regardless of the sign), the stronger the relationship. The relationship is considered acceptable if the coefficient exceeds 0.3; the higher the value, the stronger the relationship. A positive sign for the correlation coefficient indicates a positive (direct) relationship between the variables, meaning that an increase in one variable is accompanied by an increase in the other, and vice versa. On the other hand, a negative sign for the correlation coefficient indicates that the relationship is negative (inverse), meaning that an increase in one variable will be accompanied by a decrease in the other. Table (5) shows the correlation coefficient values between the twins' digital capabilities and predictive maintenance performance.

Table 5. The relationship between digital twin capabilities and predictive maintenance performance

Variables and Dimensions	Code	Statistic	Predictive Maintenance Performance (Y)
A. Real-time Monitoring	XX1	Pearson	0.535**
		Sig.	0.000
B. Digital Simulation	XX2	Pearson	0.476**
		Sig.	0.000
C. Failure Prediction	XX3	Pearson	0.436**
		Sig.	0.000
D. Intelligent Decision Making	XX4	Pearson	0.318**
		Sig.	0.007
E. Digital Integration	XX5	Pearson	0.438**
		Sig.	0.000
Digital Twin Capabilities	X	Pearson	0.606**
		Sig.	0.000

(**). Statistically significant at the 1% significance level, (*). Statistically significant at the 5% significance level
Source: Table prepared by the researcher using SPSS

Table 5 shows a statistically significant positive (direct) correlation at a significance level of less than 5% between the digital twin capabilities variable with its five dimensions (a. real-time monitoring, b. digital simulation, c. fault prediction, d. intelligent decision-making, e. digital integration) and the predictive maintenance performance variable. This indicates that the presence of the digital twin capabilities variable with its five dimensions will be accompanied by an increase in the level of predictive maintenance performance at the Samarra Thermal Power Station, an electricity generation company, according to the perception of the sample members.

5. Regression Test

This section included one main hypothesis as follows:

(H1). Main hypothesis: Digital twin capabilities have a positive and significant effect on predictive maintenance performance.

A set of sub-hypotheses stems from the main hypothesis, including:

(H11)- Real-time monitoring has a positive effect on predictive maintenance performance.
To test this hypothesis, a simple linear regression model was developed to estimate the level of predictive maintenance performance through the real-time monitoring dimension, in order to determine the extent of the latter's influence on the level of predictive maintenance performance. Table (6) shows the results of this influence.

Journal of Kyzylorda Scholarly Review
P-ISSN:3006-0265 | E-ISSN:3007-4681
https://bulletin.ouk.kz/index.php/bulletin/index.php

Table 6. The effect of digital twin capabilities on predictive maintenance performance

Hypotheses	Explanatory Variable	Dependent Variable	β0	β	T (Sig.)	F (Sig.)	R^2
H11	XX1	Y	1.849	0.517	5.216 (0.000)	27.210 (0.000)	0.286
H12	XX2	Y	2.398	0.389	4.463 (0.000)	19.921 (0.000)	0.227
H13	XX3	Y	2.679	0.311	3.990 (0.000)	15.919 (0.000)	0.190
H14	XX4	Y	3.091	0.221	2.768 (0.007)	7.662 (0.007)	0.101
H15	XX5	Y	2.724	0.318	4.012 (0.000)	16.100 (0.000)	0.191

Table 6 shows that the validity of the regression model for hypothesis (H11) is confirmed by an F-value of 27.210 at a significance level of less than 5%, indicating that the level of predictive maintenance performance can be estimated using the instantaneous observation dimension. Furthermore, the T-value of 5.216 at a significance level of less than 5% also indicates the statistical significance of the effect, whilst the positive beta coefficient (β) of 0.517 indicates that the effect is positive, meaning that the availability of the real-time monitoring dimension has a positive effect on predictive maintenance performance, as it contributes to enhancing predictive maintenance performance levels at the Samarra Thermal Power Station, the subject of this study. Furthermore, the coefficient of determination (R^2) value of (0.286) indicates that the real-time monitoring dimension explains 28.6% of the variation in the level of predictive maintenance performance, and that the remaining proportion is attributable to other factors not apparent in the current model; therefore, the first sub-hypothesis can be accepted.

(H12) Digital simulation has a positive effect on predictive maintenance performance.

To test this hypothesis, a simple linear regression model was prepared to estimate the level of predictive maintenance performance through the digital simulation dimension, in order to determine the extent of the latter's impact on the level of predictive maintenance performance. As can be seen from Table (6) that the validity of the regression model for hypothesis (H12) is confirmed by an F-value of 19.921 at a significance level of less than 5%, which means that the level of predictive maintenance performance can be estimated through the digital simulation dimension. Furthermore, the T-value of 4.463 at a significance level of less than 5% also indicates the statistical significance of the effect, whilst the positive beta coefficient (β) of 0.389 indicates that the effect is positive, meaning that the availability of the digital simulation dimension has a positive impact on predictive maintenance performance, as it contributes to enhancing predictive maintenance performance levels at the Samarra Thermal Power Station, the subject of this study. Furthermore, the coefficient of determination (R^2) value of (0.227) indicates that the digital simulation dimension explains 22.7% of the variations in the level of predictive maintenance performance, and that the remaining percentage is attributable to other factors not apparent in the current model; therefore, the second sub-hypothesis can be accepted.

(H13) The ability to predict faults has a positive effect on predictive maintenance performance.

To test this hypothesis, a simple linear regression model was prepared to estimate the level of predictive maintenance performance through the dimension of fault prediction, in order to determine the extent of the latter's influence on the level of predictive maintenance performance. As can be seen from Table (6) that the validity of the regression model for hypothesis (H13) is confirmed by an F-value of 15.919 at a significance level of less than 5%, which means that the level of predictive maintenance performance can be estimated through the dimension of fault prediction. Furthermore, the T-value of 3.990 at a significance level of less than 5% also indicates the statistical significance of the effect, whilst the positive beta coefficient (β) of 0.311 indicates that the effect is positive, meaning that the availability of the fault prediction dimension has a positive effect on predictive maintenance performance, as it contributes to enhancing predictive maintenance performance levels at the Samarra Thermal Power Station, the subject of this study. Furthermore, the coefficient of determination (R^2) value of (0.190) indicates that the fault prediction dimension explains 19% of the variation in the level of predictive maintenance performance, and that the remaining percentage is attributable to other factors not apparent in the current model; therefore, the third sub-hypothesis can be accepted.

(H14) The ability to make intelligent decisions has a positive effect on predictive maintenance performance.

To test this hypothesis, a simple linear regression model was developed to estimate the level of predictive maintenance performance through the dimension of intelligent decision-making, in order to determine the extent to which the latter influences the level of predictive maintenance performance. As can be seen from the table (6) that the validity of the regression model for hypothesis (H14) is confirmed by an F-value of 7.662 at a significance level of less than 5%, which means that the level of predictive maintenance performance can be estimated through the smart decision-making dimension. Furthermore, the T-value of 2.768 at a significance level of less than 5% also indicates the statistical significance of the effect, whilst the positive beta coefficient (β) of 0.221 indicates that the effect is positive, meaning that the presence of the smart decision-making dimension has a positive effect on predictive maintenance performance, as it contributes to enhancing predictive maintenance performance levels at the Samarra Thermal Power Station, the subject of this study. Furthermore, the coefficient of determination (R^2) value of (0.101) indicates that the smart decision-making dimension explains 10.1% of the variation in the level of predictive maintenance performance, and that the remaining proportion is attributable to other factors not apparent in the current model; therefore, the fourth sub-hypothesis can be accepted.

(H15) - Digital integration has a positive effect on predictive maintenance performance.

To test this hypothesis, a simple linear regression model was prepared to estimate the level of predictive maintenance performance through the digital integration dimension, in order to determine the extent of the latter's impact on predictive maintenance performance. As can be seen from Table (6) that the validity of the regression model for Hypothesis (H15) is confirmed by an F-value of 16.100 at a significance level of less than 5%, which means that the level of predictive maintenance performance can be estimated using the digital integration dimension. Furthermore, the T-value of 4.012 at a significance level of less than 5% also indicates the statistical significance of the effect, whilst the positive regression coefficient β of 0.318 indicates that the effect is positive, meaning that the presence of the digital integration dimension has a positive effect on predictive maintenance performance, as it contributes to enhancing predictive maintenance performance levels at the Samarra Thermal Power Station, the subject of this study. Furthermore, the coefficient of determination (R^2) value of (0.191) indicates that the digital integration dimension explains 19.1% of the variation in the level of predictive maintenance performance, and that the remaining proportion is attributable to other factors not apparent in the current model, Therefore, the fifth sub-hypothesis can be accepted, and based on the results of the sub-hypotheses, the main hypothesis of the study can be accepted.

To confirm the acceptance of the main research hypothesis, a simple linear regression model was prepared to estimate the overall performance of predictive maintenance through the variable of digital twin capabilities, in order to determine the extent of the latter's influence in this dimension; Table 7 shows the results of this influence.

Table 7. The effect of digital twin capabilities overall on predictive maintenance performance

Explanatory	**Dependent**	**(R^2)**	**(Adjusted R^2)**	**(F)**	**(Sig.)**
		0.367	0.358	39.485	0.000
		Constant Coefficient (β0)	**Regression Coefficient (β)**	**(T)**	**(Sig.)**
X	Y	1.329	0.655	6.284	0.000

Table 7 shows that the validity of the regression model is confirmed by an F-value of 39.485 at a significance level of less than 5%; this implies that the performance of predictive maintenance can be estimated using the digital twin capabilities variable. Furthermore, the T-value of 6.284 at a significance level of less than 5% indicates the statistical significance of the effect, whilst the positive beta coefficient (β) of 0.655 indicates that the effect is positive, meaning that digital twin capabilities positively influence predictive maintenance performance by enhancing predictive maintenance performance in the field under study, as perceived by the sample participants. Furthermore, the coefficient of determination (R^2) value of 0.367 that digital twin capabilities explain 36.7% of the variation in predictive maintenance performance, with the remaining proportion attributable to other factors not captured in the current model. These results confirm the rejection of the main null hypothesis and the acceptance of the main alternative hypothesis.

It can also be observed from the F-value and β-value within the five models for the sub-hypotheses that there is a difference in the level of validity of the regression model, as well as in terms of the strength of the effect. According to the validity of the regression equation model, the use of the 'instantaneous monitoring' dimension within the digital twin capabilities variable in estimating the predictive maintenance performance variable, as indicated by an F-value of 27.210, followed by the model using the 'digital simulation' dimension in estimating the predictive maintenance performance variable, as indicated by an F-value of 19.921, then the use of the 'digital integration' dimension, as indicated by an F-value of 16.100, followed by the 'Fault Prediction' dimension with an F-value of 15.919, and finally the 'Intelligent Decision-Making' dimension with an F-value of 7.662.

As for the strength of the influence of the five dimensions of the digital twin capabilities variable on the predictive maintenance performance variable, it is noted that the 'real-time monitoring' dimension had the strongest influence on the predictive maintenance performance variable, with a beta (β) value of (0.517), followed by the effect of the 'digital simulation' dimension on the predictive maintenance performance variable, with a beta (β) value of 0.389, followed by the effect of the 'digital integration' dimension, with a beta (β) value of 0.318, then the effect of the 'Fault Prediction' dimension, with a beta (β) value of 0.311, and finally the effect of the 'Intelligent Decision-Making' dimension, with a beta (β) value of 0.221.

Conclusion

1. The research findings revealed a high level of digital twin capability at the Samarra Thermal Power Station, reflecting an advanced understanding of the importance of modern digital technologies in supporting operational processes and enhancing the efficiency of industrial asset management.
2. The results indicated that the level of predictive maintenance performance in the organisation under study was high, suggesting a clear trend towards adopting proactive practices in maintenance management and reducing unplanned breakdowns and downtime.
3. The results of the statistical analysis revealed a statistically significant positive correlation between digital twin capabilities and predictive maintenance performance, confirming that enhancing digital capabilities contributes to increasing the effectiveness of predictive maintenance activities and improving their operational outcomes.
4. The results of the impact test demonstrated that digital twin capabilities have a positive and significant effect on predictive maintenance performance, indicating that investment in digital twin technologies is a key factor in developing maintenance efficiency and improving the reliability of operational assets.
5. The results showed that the fault prediction dimension achieved the highest level of availability among the digital twin capability dimensions, reflecting the organisation's ability to utilise operational data for the early prediction of technical issues and to take appropriate action before faults occur.
6. The results demonstrated that the real-time monitoring dimension is one of the most significant factors influencing predictive maintenance performance, as it contributes to providing timely and accurate information on the condition of equipment and operational assets, thereby enhancing the speed of response to operational issues.
7. The results confirmed that digital simulation is an important tool for improving predictive

maintenance operations by enabling the organisation to test different operational scenarios and evaluate alternatives before actually implementing them.

8. The results showed that digital integration between the digital twin and other operational systems helps to enhance data flow and improve the quality of information used in maintenance-related decision-making.
9. The results revealed that intelligent decision-making capability has a positive impact on predictive maintenance performance; however, its impact was less significant than that of some other dimensions, indicating further opportunities for developing artificial intelligence applications and advanced analytics within the organisation.
10. Overall, the results confirm that the digital twin represents one of the key strategic enablers for developing predictive maintenance and achieving higher levels of operational efficiency, reliability and sustainability in industrial organisations.

Second: Recommendations and Implementation Mechanisms

The study recommends expanding the use of real-time monitoring of operational equipment and assets by increasing reliance on smart sensors and the Internet of Things, through connecting all critical equipment to a centralised monitoring system that provides real-time, accurate data on their operational status.

Implementation mechanism:

Forming a specialised technical team to identify critical equipment, determine the requirements for suitable sensors, and establish a unified digital centre for the continuous monitoring and analysis of operational data.

The study recommends developing digital simulation capabilities for industrial assets to support proactive maintenance decision-making.

Implementation mechanism:

Create digital models of key equipment and use them to test potential failure scenarios and alternative maintenance plans before implementing them in the actual work environment.

The study recommends enhancing fault prediction capabilities by employing artificial intelligence and machine learning algorithms in the analysis of operational data.

Implementation mechanism:

Building a historical database of faults and maintenance and linking it to advanced analytics platforms to develop predictive models capable of detecting early failure indicators and estimating the remaining operational life of equipment.

The study recommends developing intelligent decision-support systems to help improve the quality of decisions regarding asset management and maintenance.

Implementation mechanism:

Integrating artificial intelligence tools and predictive analytics with maintenance management systems to enable the generation of automated recommendations regarding maintenance priorities and resource scheduling.

The study recommends increasing the level of digital integration between digital twin systems and maintenance, asset, and enterprise resource management systems.

Implementation mechanism:

Establishing a unified digital platform for data exchange between various operational systems and adopting standardised criteria for industrial data management.

The study recommends providing ongoing training programmes for staff in the fields of digital twins, predictive maintenance and smart analytics.

Implementation mechanism:

Organising specialised training courses and workshops in collaboration with universities and global technology companies to build staff’s digital capabilities.

The study recommends adopting an institutional strategy for digital transformation in the field of asset management and maintenance.

Implementation mechanism:

Preparing a long-term digital roadmap that includes clear objectives, performance indicators, and dedicated budgets for digital twin and smart maintenance projects.

The study recommends strengthening cooperation with universities and scientific research centres to develop digital twin applications in the energy sector.

Implementation mechanism:

Concluding joint research cooperation agreements and implementing applied projects aimed at developing advanced digital models and improving the performance of predictive maintenance in power generation plants.

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