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DEVELOPMENT OF A CONCEPTUAL FRAMEWORK FOR AN EXPLAINABLE ARTIFICIAL INTELLIGENCE-BASED PREDICTIVE MAINTENANCE DECISION SUPPORT SYSTEM FOR THE TRAFFIC ELECTRICAL INDUSTRY

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ABSTRACT

This research aims to develop a conceptual framework for an explainable artificial intelligence-based predictive maintenance decision support system (XAI-PdM DSS) for the electric traffic industry. This system uses specialized machinery that is susceptible to deterioration and unexpected downtime. The research addresses the limitations of traditional maintenance and black-box AI systems, which lack transparency in decision-making. This developmental research was conducted through a literature review on decision support systems, predictive maintenance, machinery life expectancy forecasting, explainable artificial intelligence, and multi-criteria decision techniques. This review synthesized and designed a conceptual framework that integrates AI models for machinery deterioration forecasting with machinery deterioration prediction modeling techniques to explain forecasting results. Multi-criteria decision techniques are used to prioritize maintenance tasks, presenting the results through a dashboard to support systemic decision-making. An expert evaluation of the conceptual framework by 15 individuals found it highly suitable ($\bar{x}$ = 4.23, S.D. = 0.58), indicating that the developed framework has the potential to support efficient, transparent, and practical predictive maintenance decision-making in the electric traffic industry.

Keywords: *Decision Support System; Predictive Maintenance; Explainable Artificial Intelligence; Remaining Useful Life.*

1. INTRODUCTION

The traffic light equipment manufacturing industry is a specialized production sector that plays a crucial role in urban infrastructure and public safety. It encompasses the production of key components, including streetlight and traffic signal poles, electrical control cabinets, and metal structures for street lighting systems. This requires specialized metal-forming processes and machinery, such as steel-cutting, bending, and rolling machines, to produce strong, standardized, and safe-to-use parts for outdoor environments. In particular, the production of streetlight poles is a critical process, as they are infrastructure components directly related to road user safety, the continuity of lighting systems, and the reliability of urban infrastructure. The manufacturing process requires high precision and continuous machine operation. A single error or machine failure can have a ripple effect, impacting product quality, delivery delays, production costs, and the company's image.

The traffic light industry is a manufacturing sector that relies heavily on large, highly complex machinery, which directly impacts the quality, safety, and continuity of production. However, traditional time-based maintenance fails to accurately reflect the machinery's operating conditions, leading to downtime and inefficient resource utilization [1]–[3]. Predictive maintenance and AI are used to improve the accuracy of predictions, such as fault detection and remaining-life estimates, but there are limitations in applying these results to support real-world decision-making. Furthermore, most AI models are black boxes, lacking transparency and eroding user confidence. While Explainable AI enhances the ability to explain results, it remains limited at the model level.

Traditional DSS systems cannot effectively link predictive and real-time data. Therefore, there is a need to develop a framework that integrates forecasting, explanation, and decision-making to support real-world applications and improve maintenance efficiency in the industry. To overcome the limitations of maintenance, the concept of predictive maintenance has been widely adopted in industry. It leverages artificial intelligence, machine data, and IoT technology to analyze machine condition and detect malfunctions. Predictive maintenance techniques have significantly reduced downtime, particularly through the estimation of Remaining Useful Life (RUL). This has improved resource utilization efficiency [4]. The application of Deep Learning also improves production management efficiency and reduces system disruptions [5]. Machine Learning techniques play a crucial role in detecting machine malfunctions in the operating environment, especially with large amounts of data [6]. Furthermore, predictive maintenance has been identified as a key component of Industry 4.0. It enhances machine availability, reduces long-term costs [7], and supports strategic decision-making through cost and maintenance performance analysis [8]. Integrating the Digital Twin concept with predictive maintenance improves forecasting accuracy and supports intelligent decision-making [9]. The condition-based maintenance concept reduces uncertainty in cost management [10]. The application of AI in Industry 4.0 improves the efficiency and sustainability of production processes [11]. However, research indicates that predictive maintenance systems still lack descriptive capabilities, making it difficult for users to adequately assess the reasonableness of forecasts [12],[13]. A key challenge is integrating model accuracy with the descriptive capabilities of the results [14], a limitation that remains in manufacturing systems. Interpretability must be considered alongside the model's performance [15]-[16]. Concepts and techniques for developing interpretable models of decision-making (Interpretable Machine Learning) have been introduced to increase understanding of these models' mechanics [17]. Supporting decision-making in complex contexts also requires integrating multidimensional data and using advanced analytical techniques. These steps increase system transparency [18],[19]. Therefore, integrating AI into decision-making processes remains a major challenge [20]. Explainable Artificial Intelligence concepts have been introduced to increase system transparency, clarify the rationale for forecasting results, and build user confidence in predictive maintenance systems [21],[22]. The integration of explainable AI with multi-criteria decision-making techniques helps manage decision complexity. Presenting data through dashboards supports situational awareness and operational decision-making [23],[24].

The development of a predictive maintenance decision support system framework that integrates decision support, predictive maintenance, descriptive AI, remaining machine life, and dashboard data presentation to support transparent, verifiable, and contextually relevant maintenance decision-making, leading to reduced downtime, increased machine reliability, and the sustainable advancement of maintenance processes in the traffic electrification industry towards a smart industrial system [25].

2. LITERATURE REVIEW

2.1 Decision Support System (DSS)

Decision support systems (DSSs) are developed to support decision-making in complex, multidimensional, and highly uncertain contexts. Research in this area indicates that DSSs play a crucial role in structuring information and transforming knowledge into actionable insights for systematic decision-making, especially when incorporating multi-criteria decision-making (MCDM) concepts, which enable rational and verifiable consideration of technical, economic, and operational factors. [26]–[29] MCDM research has developed various techniques to manage the uncertainty of information and expert opinions, such as Fuzzy Logic, AHP, TOPSIS, and MARCOS, which enhance the transparency and consistency of decision-making outcomes in DSSs, particularly in industrial contexts with numerous variables. [30]–[35] Furthermore, the integration of rule-based reasoning and case-based reasoning (CBR) enhances the explainability and traceability of decision-making processes, a key characteristic of highly reliable DSSs. [36]–[40]

Table 1. Synthesis of Decision Support Systems workflow

Component	**Content**	**Ref.**
Decision Support System (DSS) Foundation	This research indicates that DSS (Decision Support Systems) are systems that structure data and knowledge to support decision-making in complex situations, emphasizing the integration of multidimensional data and logical analysis.	[26],[27]
Component	**Content**	**Ref.**
Multi-Criteria Decision Making (MCDM)	MCDM is used as a core mechanism within DSS to support decision-making that requires simultaneous consideration of multiple factors, including technical, economic, and operational aspects. It helps to structure and validate decision-making.	[28],[29]
Fuzzy-based Decision Models	The application of fuzzy logic helps manage uncertainty and ambiguity, enabling DSS to accurately reflect the real-world industry environment.	[30],[31]
AHP-based Decision Support	The Analytic Hierarchy Process (AHP) technique is used to prioritize decision-making criteria and alternatives, helping to reduce bias and increase the consistency of the decision-making process in a DSS system.	[32],[33]
TOPSIS / MARCOS Techniques	The TOPSIS and MARCOS techniques are used to evaluate and rank alternatives based on their distance from the optimal alternative, thereby enhancing the transparency and rationality of the decision-making process.	[34],[35]
Rule-Based Reasoning	Rule-based reasoning enables DSS to clearly explain the rationale for decisions based on predefined logic, making it suitable for systems that require transparency and traceability.	[36],[37]
Case-Based Reasoning (CBR)	CBR supports decision-making by comparing past case studies with current situations, enabling DSS to be flexible and learn from real-world experiences.	[38],[39]
Knowledge-based DSS Limitation	Rule- and case-study-based DSSs provide substantial explanatory power. Still, research indicates limitations in handling large datasets and real-time sensor data, both of which are essential for applications in predictive maintenance systems.	[40]

A synthesis of research findings reveals that Decision Support Systems (DSSs) effectively structure information and knowledge to support decision-making in complex contexts. This is achieved by integrating multidimensional data with multi-criteria decision-making processes, thereby producing systematic, transparent, and verifiable decisions.

2.2 Predictive Maintenance

Predictive Maintenance (PdM) is an approach that uses data from machine and automation databases to assess machine condition and predict failures before they actually occur. Recent research has shown that predictive maintenance can reduce downtime, improve resource efficiency, and support maintenance planning, especially when Machine Learning and AI techniques are integrated into the data analysis process [41]–[44]. Much predictive maintenance research still focuses primarily on improving forecasting accuracy, while applying forecasts to support operational decision-making remains limited. Some research is beginning to point to the need to integrate predictive maintenance into enterprise systems and decision-making processes so that forecasts can be applied in the industrial context [45]–[48].

Table 2. Synthesis of Predictive Maintenance Workflow

Component	Content	Ref.
Predictive Maintenance (PdM) Concept	PdM is a maintenance approach that relies on data and automation to assess the condition of machinery in advance, preventing failures before they occur and reducing production downtime.	[41],[42]
AI-Driven PdM Models	The application of Machine Learning and AI in PdM enhances the accuracy of anomaly detection and prediction of machine failure trends, particularly in complex and data-intensive industrial environments.	[43],[44]
PdM Performance & Benefits	PdM can significantly reduce downtime, lower maintenance costs, and improve machine resource utilization efficiency compared to traditional maintenance.	[41]–[44]
PdM Limitation (Prediction-centric)	Although PdM is highly accurate, research indicates that most PdM development focuses primarily on forecasting results, with little linkage to practical decision-making processes at the organizational level.	[45],[46]
PdM Integration with Enterprise Systems	Some research is beginning to propose integrating PdM into enterprise-level systems, such as DSS and planning systems, so that forecasting results can be used to support maintenance decision-making.	[47],[48]
Need for Decision-Oriented PdM	The synthesis revealed that PdM still lacks a systems decision-making framework that links forecasting data to actual operations, a crucial starting point for developing a PdM that integrates DSS and XAI.	[45]–[48]

Predictive maintenance is a maintenance approach that relies on machine data, automation, and artificial intelligence models to assess machine condition in advance and reduce the risk of failure before it actually occurs. The application of AI improves the accuracy of fault detection and damage trend prediction, reduces downtime, lowers maintenance costs, and improves the efficiency of machine resource utilization compared to traditional maintenance. Research primarily focuses on predictive maintenance in a forecasting context, lacking a link between forecasting results and practical organizational decision-making. While there is a growing trend towards integrating predictive maintenance into enterprise-level systems, such as decision support systems, a systems-based decision-making framework that fully connects forecasting data with actual operations remains lacking. This reflects the need to develop a decision-making-oriented approach to predictive maintenance.

2.3 Explainable Artificial Intelligence (XAI)

Explainable Artificial Intelligence (XAI) is a concept aimed at developing AI models that can clearly explain their reasoning, decision-making processes, and the factors influencing their results, thereby increasing transparency, validation, and user understanding of the system. The XAI concept arose to overcome the limitations of black-box AI models, which, while highly accurate, lack the ability to explain their reasoning, making it difficult for users to adequately assess the validity or reliability of predictions. XAI indicates that it can explain the factors influencing prediction results and allows experts to systematically validate models.[49]–[52] Predictive Maintenance and Prognostics and Health Management (PHM) Applications: XAI techniques such as SHAP, LIME, and Rule-based Explanation are used to explain the predictive results of models and identify factors influencing machine risk or malfunction. Literature reviews indicate that these techniques have high potential to support the interpretation of model results, but their application remains largely limited to model explanation. It also lacks integration into systemic decision-making processes that link explanatory results to real-world operational contexts [53]–[55].

The research has highlighted that the ability to explain artificial intelligence results should be used in conjunction with issues of user trust and acceptance. XAI not only helps users understand the rationale behind the results but also plays an important role in increasing confidence in intelligent systems and supporting transparent, verifiable decision-making in industry contexts [56].

Table 3. Synthesis of Explainable Artificial Intelligence workflow

Component	**Content**	**Ref.**
Human-centric AI & Industry 5.0	The transition from Industry 4.0 to Industry 5.0 emphasizes human-AI collaboration to ensure intelligent systems align with human decision-making and increase industrial adoption.	[49],[50]
Explainable AI (XAI) in Industrial Systems	XAI is proposed as a key mechanism for explaining the rationale behind results from AI models in industrial systems, thereby increasing the transparency, understanding, and verifiability of automation systems.	[51],[52]
XAI for Predictive Maintenance	The use of XAI for PdM demonstrates how descriptive techniques can help experts gain a concrete understanding of the factors influencing machine failure and RUL prediction.	[53]
Systematic Review of XAI in PHM	XAI has great potential in Prognostics and Health Management (PHM), but its application is currently limited to the model level and lacks integration with system-level decision-making processes.	[54]
XAI-based PdM Frameworks	A PdM framework that integrates XAI with predictive models to support descriptive and industry-aligned decision-making for users.	[55]
Trust & Reliability in AI Predictions	The descriptive capabilities of AI should be evaluated in terms of the trustworthiness and reliability of the forecasting results to increase the system's acceptance and adoption in industry.	[56]

A synthesis of research on Explainable Artificial Intelligence (XAI) reveals a shift in industrial AI development from a focus solely on model performance to a human-centric approach. This emphasizes collaboration between humans and AI to ensure decision-making aligns with user understanding and acceptance. Research highlights XAI's crucial role in enhancing transparency, understanding, and verifiability in industrial automation, particularly in predictive maintenance, where XAI techniques concretely explain the factors that affect failure prediction and the remaining machine lifespan. However, a literature review reveals that most XAI applications remain at the model level, lacking integration with operational-level systemic decision-making. Research is beginning to propose explainable AI frameworks that integrate XAI to support explainable and user-aligned decision-making. The explainability of AI is identified as a key factor in the trustworthiness and reliability of forecasts, a crucial condition for the sustainable adoption of AI in industry.

2.4. Remaining Useful Life (RUL)

The Remaining Useful Life (RUL) estimate is a key component of predictive maintenance systems, as RUL results inform maintenance planning and strategic decision-making. Research on data presentation, dashboard design, and industrial-scale system usability evaluation shows that RULs are only truly valuable in practice when their results can be communicated effectively to users and used appropriately [57]–[59]. Integrating RULs into DSSs and presenting them through user-centric dashboards is, therefore, a key approach to elevating predictive maintenance systems from a forecasting level to a systems decision-making level, which is directly consistent with the framework of this research.

Table 4. Synthesis of the Remaining Useful Life workflow

Component	**Content**	**Ref.**
RUL as Decision-Oriented Information	RUL (Remaining Useful Life) should be presented as decision-making data that can concretely support maintenance planning and resource management at the enterprise level.	[59]
Visualization of RUL Information	Presenting RUL data on a dashboard enhances user understanding, reduces the burden of interpreting technical data, and supports situational awareness among operators in industrial environments.	[60]
User-Centered RUL Dashboard	The user-centric dashboard design indicates that RUL will have practical value only when data is presented in the user context and forecast results are clearly linked to maintenance decisions.	[61]

A synthesis of research shows that Remaining Useful Life (RUL) data for machinery should not be presented merely as numerical values from forecasting models but should be developed into decision-making information that can support maintenance planning and resource allocation at the organizational level. Research indicates that presenting RUL data through visualizations and dashboards enhances user understanding, reduces the burden of interpreting technical data, and improves situational awareness in complex industrial environments. Especially when the dashboard design is user-centric and links forecasting results to real-world decision-making contexts, RUL data will have true practical value.

The application of digital technology in the electric traffic industry enables efficient risk forecasting and proactive maintenance planning. Analyzing production data and maintenance history combined with artificial intelligence techniques increases transparency and accuracy in decision-making, resulting in reduced downtime, lower costs, and increased machinery reliability, supporting the development of the electric traffic industry towards a smart industry system.

2.5. Comparative Analysis of Existing Approaches

This section provides a comparative synthesis of existing approaches, building on the previous review. Predictive maintenance (PdM) methods are strong at forecasting machine failures and estimating remaining useful life (RUL) but lack mechanisms to apply predictions in operations. This exposes a gap between prediction results and decision implementation. AI-based PdM increases prediction accuracy, but its black-box nature limits interpretability and user confidence. While Explainable Artificial Intelligence (XAI) improves transparency by clarifying model behavior, current uses mainly explain outputs and do not fully support decisions. In contrast, Decision Support Systems (DSS), especially those using multi-criteria decision-making (MCDM), offer structured, transparent processes but typically act independently from predictive analytics and lack real-time data integration. The key issue is not their separate capabilities but the missing integration among prediction, explanation, and decision-making. This highlights the need for a unified framework combining predictive intelligence, explainability, and decision support.

Table 5. Comparative Analysis of Existing Approaches

Item	PdM	AI-based PdM	XAI	DSS (MCDM)	Proposed Framework
System Role	Condition monitoring and failure prediction of machinery	Advanced data-driven prediction using ML/AI techniques	Providing interpretability of AI model outputs	Supporting structured multi-criteria decision-making	Integrated framework combining prediction, explanation, and decision-making
Strengths	Reduces downtime, improves resource utilization, and enables accurate RUL prediction	Enhances detection of anomalies and complex patterns in	Improves transparency, interpretability, and user trust	Provides systematic, transparent, and multi-factor decision support	Seamlessly integrates predictive insights, explainability, and decision

		large-scale data			support within a unified system
Item	PdM	AI-based PdM	XAI	DSS (MCDM)	Proposed Framework
Key Limitations	Primarily prediction-oriented with limited linkage to operational decision-making	Black-box characteristics with limited interpretability	Mainly focused on model-level explanation without decision integration	Limited integration with predictive analytics and real-time data	Requires empirical validation and depends on data quality and system integration

3. METHODOLOGY

3.1 Research Design

This research uses a Design and Development Research methodology to develop a conceptual framework for an AI-assisted predictive maintenance decision support system (XAI–PdM DSS) for the electric traffic industry. The research was conducted in two main phases: (1) synthesizing knowledge and designing the system's conceptual framework, and (2) evaluating the suitability of the conceptual framework by experts. This research methodology is suitable for conceptual framework research aimed at examining the clarity, completeness, and feasibility of practical application.

3.1.1 Phase 1 of the research focused on synthesizing knowledge from research related to 1) decision support systems, 2) predictive maintenance, 3) descriptive artificial intelligence, and 4) remaining machine life. Published research from the past 5–10 years, both internationally and nationally, was selected to ensure up-to-date and comprehensive knowledge. The results of this knowledge synthesis were used to design and structure the conceptual framework for an AI-descriptive, predictive maintenance decision support system within the Input–Process–Output–Feedback (IPOF) framework. This framework comprises four main components: 1) Input data: actual operational data of the maintenance system; 2) Analysis process: the synthesis of abnormalities and maintenance decisions; 3) System output: the decision-making output; and 4) Feedback learning mechanism: the system learning mechanism that incorporates the decision-making output back into the system to improve system accuracy and provide adaptive support for real-world operations.

3.1.2. Phase 2: Expert Assessment of the Framework's Suitability

3.1.2.1. Step 1: Based on the developed framework, the researchers created a tool to assess the framework's suitability in the form of a questionnaire for experts. The questionnaire included 18 key dimensions of the system, divided into 5 dimensions:
(1) System Quality
(2) Intelligence Quality
(3) Decision Quality
(4) Learning & Adaptation Quality
(5) User & Operational Impact Quality
The questionnaire used a 5-level rating scale, from least (1) to most (5), with spaces for additional suggestions to improve the framework.

3.2 Data Collection

The data collection process in this study was conducted systematically to ensure the reliability and validity of the expert evaluation of the proposed conceptual framework. First, the researchers prepared the research instruments, which consisted of (1) the conceptual framework document of the XAI–PdM DSS and (2) a structured questionnaire designed to evaluate the suitability of the framework. The questionnaire was developed based on the key components of the IPOF model. It comprised five dimensions: system quality, intelligence quality, decision quality, learning and adaptation quality, and user and operational impact. Second, participants were selected purposively. A total of 15 experts were selected based on their professional expertise and experience in relevant domains. The expert panel consisted of three groups: (1) five maintenance experts with experience in industrial maintenance systems, (2) five artificial intelligence experts with knowledge in machine learning and explainable AI, and (3) five decision support system experts with expertise in DSS and multi-criteria decision-making. This grouping ensured comprehensive evaluation from multidisciplinary perspectives. Third, the data collection procedure was conducted online. The researchers distributed the conceptual framework document along with the evaluation questionnaire to all selected experts via electronic channels. Each expert was asked to review the framework in detail and provide an assessment on a 5-point Likert scale, ranging from 1 (lowest suitability) to 5 (highest suitability). In addition, open-ended sections were included to allow experts to provide qualitative feedback and suggestions for improving the framework. Fourth, to ensure data quality, all returned questionnaires were carefully reviewed for completeness and consistency before analysis. Only fully completed responses were included in the analysis. This process helped ensure that the collected data accurately reflected expert opinions and could be used reliably to evaluate the proposed framework. Finally, the number of experts was determined based on established methodological guidelines. Previous studies suggest that 5–10 experts are sufficient for content validity assessment, while 10–18 experts are appropriate for studies involving expert consensus. Therefore, the use of 15 experts in this study is considered adequate to provide reliable and diverse expert insights.

3.3. Data Analysis

Descriptive statistics, including the mean and standard deviation, were used to describe the appropriateness of the conceptual framework in each dimension. The interpretation criteria were as follows: a mean of 4.50–5.00 indicates very high, 3.50–4.49 indicates high, 2.50–3.49 indicates moderate, and below that, respectively.

3.4. Ethical Considerations

This research is a conceptual evaluation by experts. No personal or sensitive data was collected. All experts were informed of the research objectives, and the data collected is presented anonymously and in an undisclosed format.

4.RESULTS

4.1 System Conceptual Framework Structure

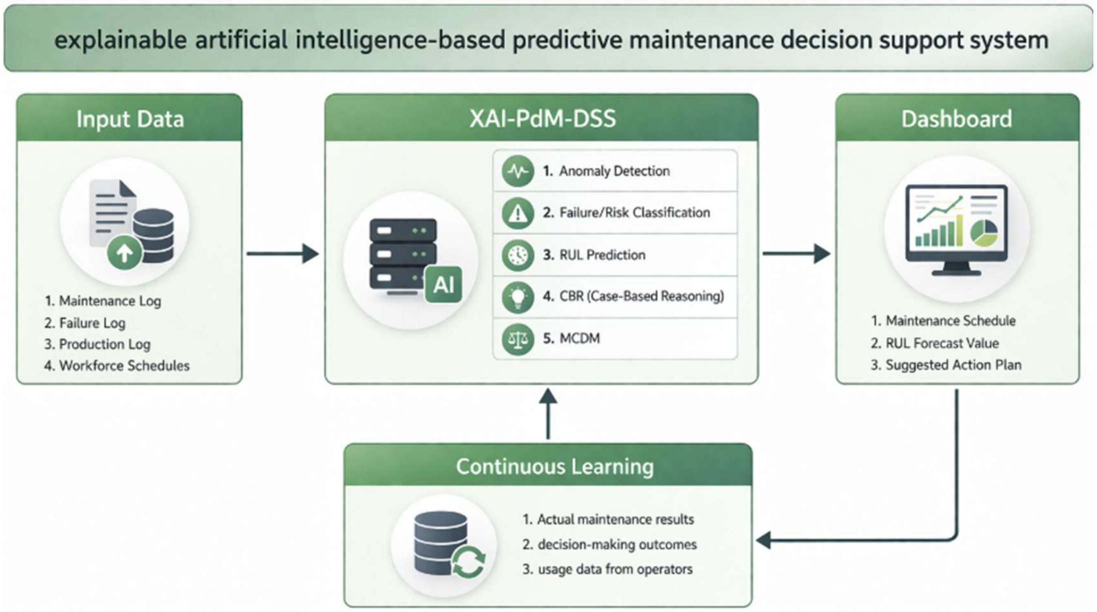

Figure 1. Conceptual Framework Of The XAI–Pdm DSS.

This image illustrates the conceptual framework of an Artificial Intelligence-Described Predictive Maintenance Decision Support System (XAI-PdM DSS), designed to operate as a systematic process from data acquisition and analysis to decision making and feedback learning

4.1.1. Input Layer: The system begins by collecting key data related to machine operation, including:

1. Maintenance Log (Maintenance History)

2. Failure Log (Failure Information)
3. Production Log (Production Data)

4.Workforce Schedules (Personnel Work Schedules)

This data serves as the primary database for predictive analysis. Using 3 years of historical data is suitable because it captures operating patterns and trends in machine degradation. This allows the model to learn from a variety of failure events, enhances the model's generalization capabilities, and reduces the risk of overfitting. As a result, the forecasting of machine risk and remaining lifespan is more accurate and consistent with actual operating conditions.

4.1.2. XAI-PdM DSS System Processing Unit: This unit is the core of the system, responsible for predictive data analysis and supporting maintenance decision-making. It comprises the following key components:

1. Anomaly Detection: This process detects machine abnormalities from operational data patterns.

Using artificial intelligence techniques to identify behaviors that deviate from normal conditions, it helps identify early warning signals and reduce the risk of damage.

2. Failure/Risk Classification: This classifies the level of risk of machine damage.

Using machine learning models to categorize operating states such as low, medium, or high risk, it helps operators assess the situation and plan maintenance appropriately.

3. RUL Prediction: This process forecasts the remaining lifespan of machinery by analyzing trends in machine degradation from historical data to predict the time when machinery may fail, supporting proactive maintenance planning.

4. Case-Based Reasoning (CBR): This analyzes solutions based on knowledge from past cases.

The system searches for cases similar to the current situation and applies previously used solutions, improving decision-making efficiency and reducing uncertainty.

5. Multi-Criteria Decision Making (MCDM): This process supports decision-making by considering various factors. Several factors, such as risk level, maintenance costs, machine importance, and production impact, must be considered to prioritize maintenance operations appropriately.

4.1.3. The Explanation and Dashboard (XAI + Dashboard) section serves as a key mechanism for presenting the results of the XAI-PdM DSS system to users, enabling them to understand and use them for effective decision-making. The system processes the analysis results from the artificial intelligence model using Explainable Artificial Intelligence (XAI) techniques to display the reasons and factors affecting the forecast in an easily understandable format.

1. Maintenance Schedule: Displays a maintenance plan recommended by the system based on the forecast results.

The machinery's risk level helps users plan maintenance appropriately and minimize its impact on the production process.

2. RUL Forecast Value: The forecast value of the remaining lifespan of the machinery, helping to estimate the time when maintenance or part replacement should be performed to prevent unexpected damage.

3. Suggested Action Plan: A suggested course of action generated by the system based on data analysis.

And past knowledge, such as preventive maintenance, production plan adjustments, or additional machinery inspections.

4.1.4. Continuous Learning: This section continuously improves the system's performance by feeding real-world data into the model's learning process to increase the accuracy and suitability of decision-making in the long term.

1. Maintenance Feedback: This refers to actual maintenance results generated after system decisions are made.

For example, maintenance outcomes, operation success, or part replacement. This data helps the system improve the accuracy of forecasting models and evaluate the effectiveness of recommendations.

2. Model Performance Evaluation: This is the process of evaluating the model's performance by comparing forecasts to actual results to analyze model errors and improve algorithms for greater accuracy and reliability.

3. User Feedback Integration: This involves incorporating user feedback into the system, such as evaluating the appropriateness of user recommendations or suggestions to improve decision criteria and align them with the actual usage context.

4. Model Update and Learning: This is the process of updating and retraining the model using the feedback received.

This allows the system to learn new anomaly patterns and adapt to changing machine operating conditions.

Therefore, the proposed system framework is a predictive decision support system that integrates data, intelligent analysis, result description, and feedback learning in a systematic and transparent manner, aligning with the approach to developing intelligent systems in the digital industrial context.

4.2 Expert Assessment of the Framework's Suitability

The assessment of the suitability of the AI-described predictive machine maintenance decision support system framework was conducted by 15 experts, comprising: 1. Five maintenance experts, 2. Five AI experts, and 3. Five decision support system experts. The assessment used a 5-level Likert-scale questionnaire covering the IPOF framework components and the system quality dimensions.

Table 6. Results Of The XAI–Pdm DSS System Suitability Assessment

No.	Evaluation list	Mean ($\bar{x}$)	S.D.	Level
1	The system can collect and display complete and accurate historical maintenance information.	4.40	0.51	Good
2	Sensor data was used for appropriate analysis.	4.20	0.68	Good
3	The system can efficiently link production data with maintenance data.	4.33	0.62	Good
4	The dashboard is clear, easy to understand, and presents complete information.	4.07	0.46	Good
	Overall average of System Quality dimensions	4.25	0.57	Good
5	The system can accurately detect machine malfunctions.	4.40	0.51	Good
6	The AI–XAI model can accurately predict remaining useful life (RUL).	4.33	0.49	Good
7	Explanations of the results using SHAP/LIME is clear and easy to understand.	4.13	0.74	Good
	Overall average of Intelligence Quality dimensions	4.29	0.59	Good
8	The AHP/TOPSIS maintenance task prioritization system provides accurate information.	4.13	0.64	Good
9	Displayed forecasts helps reduce maintenance planning time.	4.27	0.46	Good
10	Information from the system can be used to support management decision-making.	4.33	0.49	Good
	Overall average of Decision Quality dimensions	4.24	0.53	Good
11	The system can learn from past maintenance data to improve the accuracy of forecasts.	4.13	0.74	Good
12	The system can use user feedback to improve its models and decision-making.	4.40	0.63	Good
No.	Evaluation list	Mean ($\bar{x}$)	S.D.	Level
13	The system can adapt to changes in the operating conditions of the machinery.	4.27	0.59	Good

	Overall average of the Learning and Adaptation Quality dimension	4.27	0.65	Good
No.	Evaluation list	Mean ($\bar{x}$)	S.D.	Level
14	The system can actually help reduce machine downtime.	4.13	0.35	Good
15	The system helps improve the efficiency of human resource management in the maintenance department.	4.20	0.56	Good
16	The system helps reduce maintenance costs compared to the traditional method.	4.00	0.65	Good
17	The system is suitable for practical application in industrial traffic light plants.	4.20	0.56	Good
18	Overall expert satisfaction with the system.	4.13	0.64	Good
	Average of User & Operational Impact Quality dimensions.	4.13	0.55	Good
ALL	XAI–PdM DSS System Average	4.23	0.58	Good

The expert evaluation of the AI-described predictive maintenance decision support system framework revealed a high level of overall suitability, with an overall mean of ($\bar{x}$=4.23) and a standard deviation of (S.D.=0.58). This reflects the framework's structural consistency, completeness of components, and feasibility of application in the context of the traffic lighting industry. The Intelligence Quality dimension, with a mean of ($\bar{x}$ = 4.29, S.D. = 0.59), indicates that experts value the AI model's ability and Explainable AI mechanisms to detect malfunctions and predict machine lifespan, as well as the clarity of the results' explanations. This aligns with the concept of predictive maintenance research, which points out that model accuracy and the ability to explain results are crucial factors in increasing user confidence and promoting system adoption in industrial organizations. The System Quality dimension ($\bar{x}$ = 4.25, S.D.=0.57) demonstrates the system's ability to efficiently manage and present data, particularly in linking production and maintenance data. A key component of predictive maintenance systems, the Decision Quality dimension ($\bar{x}$ = 4.24, S.D.=0.53) reflects that the use of multi-criteria decision-making techniques can support the appropriate prioritization of maintenance tasks. This aligns with the Multi-Criteria Decision-Making concept used in industrial decision support systems. The User & Operational Impact Quality dimension ($\bar{x}$ = 4.13, S.D. = 0.55), while still high, reflects experts' view that practical impacts such as cost reduction, reduced downtime, and resource efficiency may require further confirmation through real-world system testing. This result aligns with research in Decision Support Systems, which indicates that assessing organizational impact requires empirical data from real-world use, which often carries more uncertainty than conceptual assessments. The Learning & Adaptation Quality dimension ($\bar{x}$ = 4.27, S.D.=0.59) demonstrates the system's ability to learn from past data and continuously improve its model. This is a crucial characteristic of modern intelligent systems that must adapt to changing operating environments, contributing to the long-term efficiency of predictive maintenance systems.

5. DISCUSSION

Research results show that the developed AI-described predictive maintenance decision support system (XAI–PdM DSS) framework can elevate the role of predictive maintenance from a mere technical analysis tool to a systematic decision support system linked to the actual operational context of the industry. This aligns with recent research trends indicating that the success of predictive maintenance should not be judged solely by the model's accuracy, but also by its ability to systematically support practical decision-making [41]–[48]. In comparison, traditional predictive maintenance approaches, which focus solely on forecasting, often lack mechanisms to link results to the decision-making process, resulting in underutilization of predictive information's value [26]–[29]. The proposed framework, however, integrates a decision support system with predictive analytics, enabling the transformation of technical data into meaningful decision-making information for users. The integration of descriptive AI into the forecasting process reduces the limitations of black-box models and enhances the user's ability to understand the rationale behind the results, a key factor in system trust and acceptance in the industrial context [53]–[56]. In comparison, predictive maintenance systems lacking descriptive capabilities, while providing accurate forecasts, are not able to effectively support decision-making. Since users are unable to adequately interpret or evaluate the reasonableness of the results, this aligns with the human-centered AI concept that emphasizes the transparency and interpretability of systems [49]–[52]. In practical applications, the developed framework can link forecast results, such as machinery's remaining life, to maintenance recommendations and plans, making the system's outputs more useful for decision-making. This aligns with findings in industrial predictive maintenance research indicating that transforming technical data into decision-making data is a key factor in decision quality and organizational efficiency [57]–[61].

5.1 Limitations and Challenges

Although the proposed XAI–PdM DSS framework shows promise, several limitations and challenges exist. First, this research covers only the development and expert evaluation of the framework; it has not been pilot-tested in a real-world environment. As a result, although experts consider the framework suitable, its effectiveness in the real world remains unconfirmed. Second, the framework assumes industry data are of high quality and fully integrated. In practice, data inconsistencies, incompleteness, and difficulties linking multiple sources can impact predictive accuracy and reliability. Third, real-world use could be limited by system complexity, computing needs, and organizational readiness—including infrastructure, technology, personnel, and processes. These components must work together for successful implementation.

5.2 Comparative Performance Analysis

To further assess the contribution of the proposed XAI–PdM DSS framework, a comparative analysis with state-of-the-art approaches is conducted across performance, efficiency, and decision-making capability. Traditional predictive maintenance (PdM) and AI-based PdM models demonstrate strong performance in fault detection and in predicting remaining useful life (RUL). However, their functionality is largely limited to analytical outputs, with minimal support for translating predictions into actionable decisions. In addition, the black-box nature of many AI models reduces interpretability and limits their practical usability in industrial contexts. In contrast, conventional Decision Support Systems (DSS) offer transparent, structured decision processes but often function without integration with predictive analytics. This separation results in slower adaptation and limited responsiveness to dynamic, real-time operational conditions. The proposed framework addresses these gaps by integrating predictive analytics, Explainable Artificial Intelligence (XAI), and decision-support mechanisms into a unified workflow. This integration enhances transparency, reduces the gap between data analysis and operational action, and supports more informed decision-making. The expert evaluation results ($\bar{x}$ = 4.23, S.D. = 0.58) further indicate a good level of suitability, particularly in intelligence and decision quality. In summary, while the proposed framework demonstrates strong conceptual potential and addresses previous gaps, further real-world implementation is necessary to confirm its operational effectiveness.

6. CONCLUSION AND FUTURE WORK

This research presents an AI-based predictive maintenance decision-support system framework for the traffic light equipment manufacturing industry. This specialized industry requires high levels of process continuity and machine reliability. The system uses three years of historical machine operation data as a base for analyzing and learning patterns of malfunctions, degradation trends, and machine failure events. The developed framework integrates predictive maintenance analysis with AI outcome description mechanisms and decision support processes within a closed-loop structure capable of continuous learning and system improvement. The results show that designing a system that links predictive results with outcome descriptions and practical recommendations significantly enhances transparency, interpretability, and user trust in the system. The proposed framework thus elevates the role of predictive maintenance from a technical analysis to a human-centered decision-support system, making it appropriately applicable in specific industrial contexts**.**

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