Journal of Economics, Finance and Management Studies

ISSN (print): 2644-0490, ISSN (online): 2644-0504

Volume 08 Issue 08 August 2025

Article DOI: 10.47191/jefms/v8-i8-70, Impact Factor: 8.317

Page No: 5772-5785

AI-Based Predictive Maintenance in Computer Engineering: Enhancing System Reliability Under the Moderating Role of Edge Computing Integration

Hoang Minh Quan[1], Tran Minh Khang[2]

[1]Faculty of Business Management, University of Greenwich, London, UK

[2]Saddleback College, California, US

ABSTRACT: In the era of digital transformation, ensuring high system reliability in computer engineering has become a critical priority, particularly in distributed and resource-constrained environments. Artificial Intelligence (AI)-based predictive maintenance, and specifically Failure Pattern Detection via Machine Learning (FPDML), offers a proactive approach to fault management by identifying anomalies before they cause system downtime. However, the effectiveness of these strategies is influenced by real-time data processing capabilities, with Edge Computing Integration (ECI) emerging as a key enabler to reduce latency, enhance fault tolerance, and strengthen operational continuity. This study employs a quantitative research design to examine the impact of AI-based predictive maintenance on system reliability, with FPDML as a core mechanism and ECI as a moderating variable. Drawing on Reliability Theory, Edge AI, and Distributed System Reliability frameworks, the research analyzes responses across Vietnam, Singapore, and Malaysia, including system engineers, IT administrators, operations managers, and policy researchers. Data was collected using a structured 5-point Likert-scale survey and analyzed to assess direct and moderated relationships among variables. The findings are expected to provide empirical evidence on how AI-driven maintenance strategies, when integrated with edge computing, can significantly improve system uptime, reduce unplanned outages, and optimize resource usage in complex computing environments. The study also addresses practical challenges such as model interpretability, data quality, and cybersecurity, offering insights for both industry practitioners and policymakers aiming to enhance the reliability of next-generation distributed systems.

KEYWORDS: AI-based predictive maintenance; Edge computing; Failure pattern detection; System reliability; Real-time anomaly detection.

1. INTRODUCTION

In the era of digital transformation and automation, computer engineering systems are increasingly critical to industrial and technological operations, demanding high reliability to ensure uninterrupted performance (Yu et al., 2023). The integration of artificial intelligence (AI) into predictive maintenance has emerged as a transformative approach, leveraging machine learning to detect failure patterns and proactively mitigate risks, thereby enhancing system reliability and optimizing operational efficiency (Rayhana et al., 2024). However, the effectiveness of AI-based predictive maintenance often hinges on real-time data processing capabilities, particularly in distributed environments where traditional cloud-based systems face latency and bandwidth constraints (Zhang et al., 2025).

Despite these advancements, significant challenges persist in fully harnessing AI-based predictive maintenance to improve system reliability. Existing research often focuses on either AI-driven maintenance or edge computing in isolation, with limited empirical exploration of how edge computing integration moderates the relationship between predictive maintenance and system reliability in complex, distributed computer engineering systems (Artiushenko et al., 2023). Issues such as model interpretability, data quality, cybersecurity, and scalability further complicate practical deployment, creating a critical research gap in understanding their synergistic effects (Mikolajewska et al., 2025).

This study aims to address this gap by investigating the impact of AI-based predictive maintenance, specifically failure pattern detection via machine learning, on system reliability in computer engineering, with a focus on the moderating role of edge computing integration. By leveraging real-world datasets and advanced analytical methods, the research seeks to propose optimized technological solutions for enhancing system reliability in distributed environments. To guide this investigation, the study addresses the following research questions: (1) To what extent does AI-based predictive maintenance, through failure pattern detection, enhance system reliability in computer engineering systems?; (2) How does edge computing integration moderate the relationship between AI-based predictive maintenance and system reliability?; (3) What are the key challenges (e.g., model interpretability, cybersecurity, scalability) in implementing AI-based predictive maintenance with edge computing integration, and how can they be addressed to optimize system reliability?

2. LITERATURE REVIEW

2.1 System Reliability in Computer Engineering

System reliability in computer engineering refers to the system's capacity to operate consistently without failure over a defined period under specific conditions (Mittal and Vetter, 2015). Traditionally, reliability has been a core objective in system design, emphasizing hardware durability, software stability, and fault tolerance. It is commonly measured using technical metrics such as Mean Time Between Failures (MTBF), failure rates, and system uptime, which together provide a quantitative basis for evaluating the stability and dependability of computing systems (Alavian et al., 2020; Duer et al., 2023). A reliable system reduces downtime, enhances operational continuity, and strengthens user trust in digital infrastructure.

In recent years, the concept of system reliability has expanded beyond basic fault resistance to encompass intelligent, predictive, and adaptive capabilities largely enabled by AI-based technologies. Predictive maintenance powered by AI, for instance, represents a shift from reactive to proactive reliability management. By using machine learning models to detect failure patterns, anticipate risks, and automate maintenance decisions, system reliability now involves continuous learning and optimization (Li et al., 2022; Xu et al., 2022).

Within the field of computer engineering, especially in mission-critical environments like industrial automation or cloud systems, ensuring high system reliability is essential. Predictive algorithms can identify early warning signs in sensor data, enabling preemptive action and improving uptime. For example, AI-based diagnostics have significantly improved Mean Time Between Failures (MTBF) and reduced unplanned outages in industrial settings by enabling earlier detection of faults and more accurate prediction of equipment failures. By leveraging real-time telemetry data and advanced machine learning algorithms, these systems can identify anomalies, predict potential future failures, and support proactive maintenance decisions, which leads to increased maintenance efficiency and minimized downtime (Farooq et al., 2025; Habyarimana and Adebiyi, 2025).

In the broader technological context, system reliability contributes to sustainable digital infrastructure. As edge computing becomes increasingly integrated, reliability gains further importance by enabling real-time, decentralized failure detection and autonomous system recovery, fostering resilience in distributed environments.

2.2 Anchoring Theoretical Framework

2.2.1 Reliability Theory

Reliability Theory is a key engineering framework for analyzing how well systems both hardware and software can function without failure over a set period under defined conditions, providing a quantitative basis for assessing system performance by modeling the probability of failure, accounting for uncertainties in loads, material properties, and operational environments through probabilistic and statistical methods (Zio, 2009). It uses probabilistic models to estimate failure rates, MTBF, and system uptime through tools like Reliability Block Diagrams (RBDs), Fault Tree Analysis (FTA), and Failure Mode and Effects Analysis (FMEA). These tools help identify failure points, evaluate their impact, and model system degradation caused by aging or wear using physical-statistical methods (Kabir and Papadopoulos, 2018). Originally developed in engineering, Reliability Theory is now widely used to ensure dependable performance across various systems, including complex computing environments.

In the field of AI-based predictive maintenance, Reliability Theory provides a structured and practical approach for evaluating and improving system performance over time. It helps explain why failures happen and how to prevent them, using models such as Mean Time Between Failures (MTBF) and Fault Tree Analysis (FTA) to guide predictive strategies (Kabir and Papadopoulos, 2018). For instance, machine learning algorithms trained on historical failure data can forecast when specific components are likely to wear out, allowing for timely maintenance that extends system lifespan and improves reliability metrics like MTBF. The theory also offers valuable insights into how edge computing can influence system reliability. Since edge computing processes data closer to the source, concepts like fault tolerance and system redundancy become vital. These principles help evaluate how spreading AI tasks across multiple edge devices reduces the chances of complete system failure and increases overall uptime (Sun et al., 2020; Zhang et al., 2024). This is particularly relevant in distributed environments, where systems must perform reliably even with limited resources. Research consistently highlights the value of Reliability Theory in strengthening system performance within computer engineering. For instance, Sathupadi et al. (2024) show that when predictive maintenance is implemented through a hybrid edge-cloud framework, system performance significantly improves due to faster anomaly detection at the edge and accurate failure prediction in the cloud. This synergy reduces latency by up to 35%, decreases energy consumption by 28%, and optimizes bandwidth usage by 60%, contributing to increased system uptime and operational efficiency.

Reliability Theory serves as a critical lens to examine the relationship between AI-based predictive maintenance and system reliability, with edge computing integration as a moderating variable. By providing a framework to quantify failure rates and system uptime, the theory supports the hypothesis that AI-driven failure pattern detection significantly enhances system reliability (H1: AI-based predictive maintenance positively impacts system reliability in computer engineering). Additionally, the theory's emphasis on distributed system architectures underpins the hypothesis that edge computing strengthens this relationship by enabling real-time fault detection and fault-tolerant mechanisms (H2: Edge computing integration positively moderates the relationship between AI-based predictive maintenance and system reliability). However, Reliability Theory assumes that failure patterns follow predictable probabilistic distributions, which may not always hold in highly dynamic or heterogeneous computing environments, potentially limiting its applicability. Furthermore, the theory does not inherently address challenges such as model interpretability or cybersecurity in AI-driven systems, which must be considered to ensure robust application in real-world settings (Sarker et al., 2024; Rjoub et al., 2023). These assumptions and limitations highlight the need for empirical validation using real-world datasets to refine the theory's application in the context of edge-enabled AI maintenance systems.

2.2.2 Edge AI and Machine Learning at the Edge

Edge AI and Machine Learning at the Edge refer to the deployment of AI and machine learning algorithms on resource-constrained edge devices located near the data source, enabling real-time data processing without relying on centralized cloud infrastructure (Merenda, Porcaro, and Iero, 2020). This framework focuses on optimizing lightweight models such as TensorFlow Lite and Core ML for low-power, low-latency environments, leveraging the advancement of IoT and distributed computing. Key benefits include reduced latency, improved data privacy, and enhanced responsiveness essential for applications like predictive maintenance and failure detection in computer engineering systems (Sathupadi et al., 2024).

In the context of AI-driven predictive maintenance, Edge AI provides a practical framework for detecting failure patterns and executing maintenance strategies directly on edge devices. This enables localized, real-time analysis of data such as sensor outputs or performance logs to anticipate failures before they occur, thus improving system reliability (Sathupadi et al., 2024). For example, edge-deployed ML models can identify anomalies in hardware or software components, reducing latency from 200 ms in cloud-based systems to as low as 50 ms (Roche et al., 2023; Reis and Serôdio, 2025). Moreover, Edge AI supports distributed processing, which helps mitigate network congestion and strengthens fault tolerance, aligning with the research goal of optimizing real-time system maintenance in distributed environments (Shi et al., 2020).

Empirical evidence supports the effectiveness of Edge AI in enhancing system reliability. Rayhana et al. (2024) report that edge-based AI models achieve 95% accuracy in failure detection, with up to 75% latency reduction compared to cloud approaches. A review by ScienceDirect (2023) also confirms that edge-based machine learning systems can achieve nearly equivalent accuracy to cloud-based models (95.1% vs. 96.1%), while significantly reducing inference time (0.2s compared to 2s). This makes edge computing a more viable solution for real-time automation environments where low latency is critical (Shah et al., 2022).

This theoretical lens also underpins the hypothesis that edge computing positively moderates the relationship between AI-based predictive maintenance and system reliability (H3). It assumes edge devices have sufficient computational capacity and consistent data quality across distributed systems. Nonetheless, several limitations remain, including challenges in model interpretability, cybersecurity risks, and the need for energy-efficient algorithms suited for constrained devices (Tu et al., 2024; Ferrag et al., 2023). These factors warrant further empirical research to assess the scalability, reliability, and security of Edge AI when integrated into real-world predictive maintenance systems.

2.2.3 Distributed System Reliability

Distributed System Reliability is a theoretical framework that focuses on ensuring the consistent and dependable operation of systems composed of multiple interconnected components, such as those in edge computing environments. It emphasizes mechanisms like redundancy (e.g., parallel redundancy), fault tolerance (the ability to maintain functionality despite component failures), and consensus algorithms (e.g., Paxos, Raft) to ensure system integrity and minimize disruptions (Ahmed and Wu, 2013). The theory addresses challenges such as single points of failure, communication delays, and resource constraints by designing robust architectures and energy-efficient protocols. Originating from distributed computing research, this framework is critical for systems where components operate across geographically dispersed or resource-limited environments, as highlighted in studies on edge computing reliability (Elbamby et al., 2019).

In the context of AI-based predictive maintenance in computer engineering, Distributed System Reliability provides a foundation for understanding how edge computing integration enhances system reliability in distributed environments. For instance, if an edge device fails, redundant nodes can assume its tasks, ensuring continuous operation and supporting AI-driven failure pattern detection to maintain system uptime. Additionally, lightweight consensus algorithms and energy-efficient communication protocols enable reliable data exchange among edge devices, mitigating the impact of network delays and resource constraints (Savaglio et al., 2019). This framework is particularly relevant for analyzing the moderating role of edge computing, as it explains how distributed architectures enhance the effectiveness of AI-based predictive maintenance in achieving higher system reliability.

Empirical research supports the effectiveness of Distributed System Reliability in enhancing system performance in edge computing environments. Similarly, Yu et al. (2023) show that Edge-based predictive maintenance systems that leverage distributed and modular architectures, such as fog and IIoT gateways, enhance equipment reliability by enabling local, real-time fault detection and autonomous operation. These systems reduce unplanned downtime, improve responsiveness, and support continuous asset monitoring, even when disconnected from central networks (Resende et al., 2021; Teoh et al., 2023). Furthermore, A comprehensive framework for In-Edge AI based on Deep Reinforcement Learning and Federated Learning demonstrates how distributed learning architectures can enhance system adaptability and robustness in mobile edge computing. By enabling decentralized model training and collaborative decision-making among edge nodes, the framework improves reliability and responsiveness in real-time applications such as caching and computation offloading (Wang et al., 2019). These findings underscore the theory's relevance to the research context.

Distributed System Reliability provides a critical lens for examining how edge computing integration moderates the relationship between AI-based predictive maintenance and system reliability. By emphasizing fault tolerance and redundancy, the theory supports the hypothesis that AI-driven predictive maintenance enhances system reliability in computer engineering (H1: AI-based predictive maintenance positively impacts system reliability in computer engineering). Additionally, it underpins the hypothesis that edge computing strengthens this relationship by enabling robust, distributed architectures that mitigate failures (H2: Edge computing integration positively moderates the relationship between AI-based predictive maintenance and system reliability). The theory assumes that edge devices operate with sufficient redundancy and reliable communication protocols, which may not always hold in highly heterogeneous or resource-scarce environments. Limitations include challenges in implementing scalable consensus algorithms and addressing cybersecurity risks in distributed systems, which could impact reliability (Ahmed and Wu, 2013).

2.3 Determinants of System Reliability in Computer Engineering

2.3.1 AI-Based Predictive Maintenance (AIPM)

AI-Based Predictive Maintenance refers to the application of artificial intelligence (AI) and machine learning (ML) techniques to anticipate and mitigate potential system failures in computer engineering systems by analyzing historical and real-time data to detect failure patterns (Ochella, Shafiee and Dinmohammadi, 2022). This approach shifts maintenance from reactive or scheduled strategies to proactive interventions, aiming to minimize downtime, extend component lifespan, and optimize operational efficiency. By leveraging machine learning algorithms, such as those for failure pattern detection, AI-based predictive maintenance identifies anomalies and predicts failure risks, enabling timely interventions (Mohammed et al., 2019). In the context of computer engineering, this concept is critical for ensuring system reliability in complex, automated environments where uninterrupted operation is paramount, particularly when integrated with edge computing for real-time processing (Liu et al., 2018).

AI-Based Predictive Maintenance can be analyzed through three philosophical lenses to deepen its theoretical grounding. From an ontological perspective, the approach assumes that system failures follow identifiable patterns embedded in data, which AI can uncover to predict and prevent disruptions (Ucar, Karakose and Kırımça, 2024; Stohr et al., 2024). This perspective posits that reality in computing systems is measurable and predictable through data-driven models. From an epistemological perspective, the knowledge generated by AI-based predictive maintenance relies on iterative learning from empirical data, validated through ML models like neural networks or decision trees, which improve prediction accuracy over time (Bouabdallaoui et al., 2021). This aligns with a positivist approach, emphasizing empirical validation of failure predictions. From an axiological perspective, the value of AI-based predictive maintenance lies in its ability to enhance system reliability while optimizing resource use and reducing costs, aligning with utilitarian principles of maximizing operational efficiency and societal benefits in industrial settings (Çınar et al., 2020). These perspectives collectively underscore the theoretical robustness of AI-based predictive maintenance in computer engineering.

The academic discourse on AI-Based Predictive Maintenance reveals both its potential and contentious issues, highlighting research gaps. Proponents argue that AI-driven approaches significantly enhance system reliability in industrial environments by enabling accurate fault pattern detection and timely maintenance interventions. In maritime predictive maintenance, machine learning algorithms such as k-nearest neighbors (kNN) have proven effective in identifying early signs of failure, supporting real-time diagnosis, and improving operational efficiency and equipment safety (Simion et al., 2024). However, critics highlight challenges in model interpretability, where complex ML models like deep neural networks may act as "black boxes," limiting trust in their predictions (Carvalho et al., 2019; Burkart and Huber, 2020). Additionally, data quality issues, such as incomplete or noisy datasets, can undermine prediction accuracy, while cybersecurity risks in AI deployments pose threats to system integrity (Ucar, Karakose, and Kırımça, 2024). These conflicting perspectives reveal a research gap in empirically validating the synergistic effects of AI-based predictive maintenance and edge computing, particularly in addressing interpretability, cybersecurity, and scalability in distributed environments.

In a practical context, AI-Based Predictive Maintenance can be illustrated through its application in a distributed computer engineering system, such as an industrial IoT network for manufacturing. For example, factories that deploy edge devices integrated with machine learning models can monitor equipment sensors in real time to detect anomaly patterns such as unusual vibration or overheating enabling proactive component replacement before failure occurs. By combining sensor data analysis with distributed architectures, these predictive maintenance systems improve operational efficiency and reduce unplanned downtime, as demonstrated in industrial IoT use cases (Rosati et al., 2023; Liu et al., 2021). This case bridges theory and practice, demonstrating how AI-based predictive maintenance enhances system reliability in real-world applications while highlighting the moderating role of edge computing in enabling real-time, distributed solutions.

H1: AI-based predictive maintenance positively impacts system reliability in computer engineering.

2.3.2 Failure Pattern Detection via Machine Learning (FPDML)

Failure Pattern Detection via Machine Learning (FPDML) refers to the use of machine learning to spot patterns in system data that signal potential failures, allowing for timely and preventive maintenance in computer engineering systems (Mohammed et al., 2019). By applying methods like anomaly detection, classification, and predictive modeling, FPDML analyzes both past and real-time data from hardware and software to anticipate faults before they happen. This approach lies at the heart of AI-driven predictive maintenance, helping to minimize system downtime, improve overall performance, and extend the life of critical components in complex computing environments. When combined with edge computing, FPDML becomes even more valuable by enabling immediate fault detection directly on low-power, resource-limited devices. This real-time responsiveness is essential to the research goal of enhancing system reliability across distributed, decentralized computing settings.

Failure Pattern Detection via Machine Learning (FPDML) can be explored through three key philosophical perspectives, offering a solid theoretical foundation. Ontologically, FPDML is grounded in the belief that failure patterns are intrinsic to computer systems and can be systematically identified through data, suggesting that system behavior is observable and predictable through measurable indicators (Ucar, Karakose, and Kırımça, 2024). From an epistemological standpoint, FPDML produces knowledge through iterative learning processes using algorithms such as neural networks and decision trees that refine their predictions based on empirical data (Mohammed et al., 2019). This reflects a positivist worldview, emphasizing evidence-based understanding and validation. Axiologically, the significance of FPDML lies in its practical benefits enhancing reliability and efficiency in computing systems. It aligns with utilitarian values by reducing failures, minimizing downtime, and promoting efficient resource use, particularly in industrial and distributed environments (Wang et al., 2022). Together, these perspectives underscore the philosophical and practical relevance of FPDML within predictive maintenance frameworks.

The academic discourse on FPDML reveals both its strengths and challenges, exposing research gaps. FPDML's effectiveness depends on high-quality, comprehensive datasets, and issues like noisy or incomplete data can compromise accuracy (Ucar, Karakose, and Kırımça, 2024). The integration of FPDML with edge computing further fuels debate, as it enables low-latency processing but introduces challenges in scalability and cybersecurity, particularly in resource-constrained environments (Aral and Brandić, 2021). These conflicting views underscore a research gap in empirically exploring the combined effects of FPDML and edge computing on system reliability, particularly regarding interpretability, data quality, and secure implementation.

In practice, FPDML can be applied in distributed systems like smart manufacturing, where edge-enabled IoT devices run ML models (e.g., TensorFlow Lite) to analyze real-time data such as CPU temperature or disk activity. This example shows how FPDML translates predictive insights into real-world system reliability improvements, especially when supported by edge computing.

H2: Failure pattern detection via machine learning positively impacts system reliability in computer engineering.

2.3.3 Moderating Role of Edge Computing Integration (ECI)

Edge Computing Integration (ECI) refers to the incorporation of edge computing architectures into computer engineering systems to enable localized data processing and real-time decision-making, particularly in the context of AI-based predictive maintenance (Resende et al., 2021; Yu et al., 2022). ECI serves as a moderating variable by enhancing the relationship between AI-based predictive maintenance, including failure pattern detection via machine learning, and system reliability. By deploying AI algorithms on edge devices, ECI reduces latency, minimizes network dependency, and supports fault-tolerant operations, thereby amplifying the effectiveness of predictive maintenance in improving system uptime and reliability (Yu et al., 2022). The role of ECI is to facilitate real-time, distributed processing, which is critical for time-sensitive applications in complex computing environments, ensuring that predictive maintenance strategies achieve optimal outcomes in enhancing system reliability (Yu et al., 2022).

The moderating role of ECI is grounded in two key theoretical frameworks: Edge AI and Machine Learning at the Edge and Distributed System Reliability. Distributed System Reliability complements this by providing concepts like redundancy and fault tolerance, which ensure that edge computing architectures maintain system integrity even when individual nodes fail, thus amplifying the reliability benefits of predictive maintenance (Mudassar, Zhai and Lejian, 2022; Sun et al., 2020). Together, these theories underpin ECI's moderating effect by enabling robust, distributed processing environments that optimize the application of AI-driven maintenance strategies to achieve higher system reliability (Ucar, Karakose and Kırımça, 2024).

The academic discourse on ECI as a moderator reveals both its potential and challenges, highlighting research gaps. Proponents argue that The integration of Edge Computing Infrastructure (ECI) significantly enhances the synergy between AI-based predictive maintenance and system reliability by enabling real-time data processing and reducing latency compared to traditional cloud-based architectures. Recent studies have demonstrated that AI-driven predictive maintenance, particularly through deep learning models, can achieve failure detection accuracies exceeding 90%. Bidollahkhani and Kunkel (2024) highlight how ECI, in combination with scalable AI technologies, plays a pivotal role in optimizing maintenance strategies, minimizing downtime, and addressing the latency challenges inherent in distributed computing environments. However, critics point out that ECI introduces complexities, such as scalability limitations and cybersecurity vulnerabilities, particularly in resource-constrained edge environments (Artiushenko et al., 2023). Additionally, the effectiveness of ECI depends on high-quality data and robust model implementation, and issues like noisy datasets or inadequate computational resources can undermine its moderating impact (Ucar, Karakose, and Kırımça, 2024). Few studies have empirically examined ECI's specific role in moderating the relationship between AI-based predictive maintenance and system reliability in distributed computer engineering systems, creating a research gap in understanding its synergistic effects and addressing practical deployment challenges like interpretability and cost-efficiency.
H3: Edge computing integration positively moderates the relationship between AI-based predictive maintenance and system reliability in computer engineering.

Building on a robust theoretical foundation, this study enhances its academic contribution by advancing the following conceptual framework.

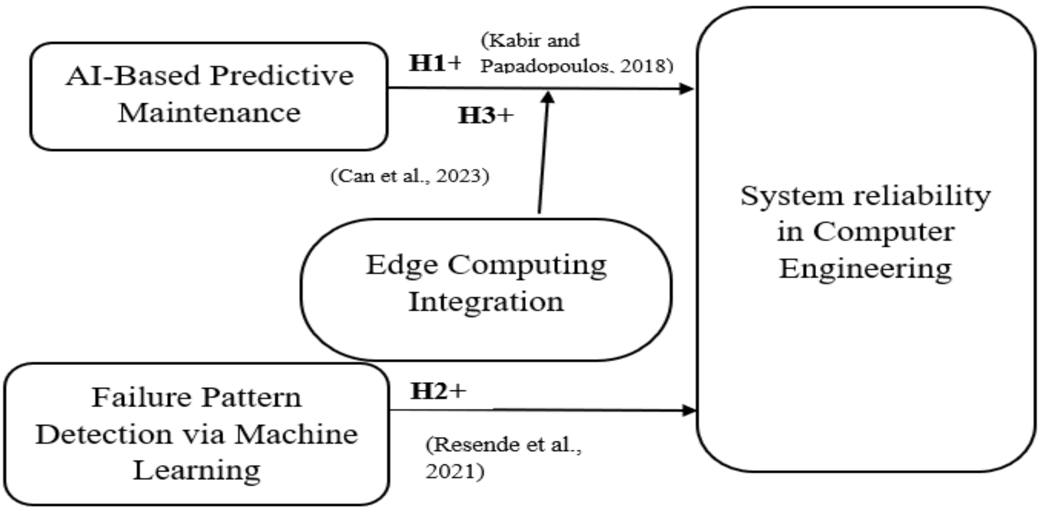

Figure 1. Conceptual Framework

Source: *(The authors, 2025)*

3. METHODOLOGY

This study adopts a quantitative research design to examine the relationship between AI-based predictive maintenance specifically failure pattern detection via machine learning and system reliability, with edge computing integration as a moderating factor. Purposive stratified sampling was employed to ensure representation from diverse professional and technical backgrounds directly involved in the deployment, management, and optimization of predictive maintenance systems in distributed computer engineering environments.

Participants were drawn from three regions Vietnam, Singapore, and Malaysia selected for their rapid adoption of Industry 4.0 technologies, strong ICT infrastructure, and increasing integration of AI-driven maintenance in industrial and commercial sectors. The sample was stratified into four equally represented stakeholder groups: (1) system engineers and data scientists developing AI-based predictive maintenance algorithms; (2) IT infrastructure and network administrators managing edge-computing-enabled systems; (3) operations and maintenance managers responsible for implementing predictive maintenance strategies in industrial or enterprise environments; and (4) academic researchers and policy analysts specializing in system reliability, AI deployment, and digital infrastructure governance.

Eligibility criteria required participants to have at least one year of professional experience in AI-based predictive maintenance or related fields, direct involvement in failure detection, anomaly monitoring, or system reliability optimization, and familiarity with distributed or edge computing environments. Data was collected via an online structured questionnaire using a 5-point Likert scale (1 = "Strongly disagree" to 5 = "Strongly agree"), targeting three primary constructs: AI-based predictive maintenance effectiveness, perceived system reliability improvements, and the moderating role of edge computing integration. The survey was distributed through professional networks, industrial associations, research institutes, and online communities focused on predictive maintenance and edge computing technologies. In Vietnam, outreach was supported by partnerships with the Vietnam National Institute of Software and Digital Content Industry (NISCI) and university research labs specializing in industrial AI. In Singapore and Malaysia, dissemination was facilitated through regional ICT industry associations, edge computing working groups, and LinkedIn professional communities in AI engineering and industrial automation. A total of 524 responses were received, with 385 valid cases retained after screening for completeness, relevance, and role-specific expertise. The balanced distribution across stakeholder categories and countries ensures a robust empirical foundation for examining how AI-driven failure pattern detection and edge computing integration jointly influence system reliability in computer engineering.

4. RESULTS

4.1. Reliability analysis

Table 1: Reliability analysis of "System reliability in computer engineering". Source: (The authors, 2025)

Reliability Statistics

Cronbach's Alpha	N of Items
.745	4

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
SRCE1	8.008	9.918	.602	.720
SRCE2	8.625	7.701	.659	.695
SRCE3	7.772	7.993	.646	.672
SRCE4	8.580	9.115	.623	.673

Where survey items SRCE1–SRCE4 were assigned to the four survey items representing the dependent variable respectively. As presented in Table 1, all dependent sub-variables recorded adjusted item–total correlations of at least 0.3. The overall Cronbach's alpha coefficient was 0.745, surpassing the generally accepted minimum threshold of 0.7 and higher than any alternative alpha values that would have emerged if individual items had been excluded. Furthermore, each sub-item exhibited a Cronbach's alpha greater than its respective adjusted item–total correlation, even when assessed independently. Accordingly, all four items were judged reliable and retained for further analysis. Comparable internal consistency was likewise evident in the Cronbach's alpha results of the other constructs.

4.2. Exploratory factor analysis (EFA)

Table 2: Rotated Component Matrix. Source: (The authors, 2025)

Rotated Component Matrix[a]			
Component with loading factors			
1	2	3	4
SRCE1 .528 SRCE2 .569 SRCE3 .600 SRCE4 .680	PM1 .555 PM2 .584 PM3 .597 PM4 .613	FPDML1 .633 FPDML 2 .537 FPDML 3 .648 FPDML 4 .650	ECI1 .669 ECI2 .612 ECI3 .639 ECI4 .772
Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.			
a. Rotation converged in 7 iterations.			

Where survey items PM1–PM4, FPDML1–FPDML4, and ECI1–ECI4 were constructed to measure the two independent variables and the moderator, with four questions allocated to each construct.

As reported in Table 2, the rotated component matrix effectively grouped the 16 sub-items into four distinct factors that corresponded precisely to the dependent variable, the two independent variables, and the moderator. All items exhibited factor loadings above the 0.5 threshold, confirming their suitability for their respective constructs. Consequently, no items were removed during factor analysis, thereby demonstrating strong construct validity across all variables.

4.3. Multiple linear regression model

Table 3: Coefficients[a]. Source: (The authors, 2025)

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
	(Constant)	5.373	.638		4.912	.000
1	PM	.768	.623	.753	3.605	.000
	FPDML	.672	.553	.665	3.467	.000

a. Dependent Variable: SRCE

Where **SRCE**: mean of SRCE 1 to SRCE 4; **FPDML**: mean of FPDML 1 to FPDML 4; **PM**: mean of PM1 to PM4

As indicated in Table 3, the t-test yielded significance (Sig.) values of .000, which fall below the conventional alpha level of 0.05. This outcome demonstrates that the independent variables have a statistically significant impact on the dependent variable. Accordingly, both proposed hypotheses are empirically supported.

4.4. Moderator analysis

Table 4: Results analysis of "Edge Computing Integration". Source: (The authors, 2025)

Model : 1
Y : SRCE
X : PM
W : ECI
Sample Size: 385

****

OUTCOME VARIABLE:
SRCE
Model Summary

R	R-sq	MSE	F	dl1	dl2	p
.813	.661	.623	5.910	3.000	381.000	.000

Model

	coeff	se	t	p	LLCI	ULCI
constant	7.273	.576	60.030	.000	7.865	8.731

PM	.529	.700	4.543	.000	.633	.619
ECI	.538	.699	4.715	.000	.755	.737
Int_1	.501	.742	4.608	.000	.746	.741

Where **ECI**: mean of ECI 1 to ECI 4

As presented in Table 4, the p-value associated with the interaction term (Int_1) is 0.000, well below the standard significance threshold of 0.05. This confirms a statistically significant interaction between Edge Computing Integration and AI-Based predictive maintenance in influencing system reliability in computer engineering. The interaction coefficient of 0.501 further indicates that stronger Edge Computing Integration amplifies the positive effect of AI-Based predictive maintenance on system reliability in computer engineering. Hence, hypothesis H3 is empirically supported.

5. DISCUSSION

AI-Based Predictive Maintenance (β = 0.753) and Failure Pattern Detection via Machine Learning (β = 0.665) both exert significant positive effects on system reliability in computer engineering. Moreover, Edge Computing Integration act as a moderating factor, strengthening the relationship between AI-Based predictive maintenance and system reliability in computer engineering, as reflected by a moderation coefficient of 0.501.

5.2. Theoretical Implication

The findings provide strong evidence that AI-based predictive maintenance substantially improves system reliability, supporting prior research that emphasizes its proactive contribution to fault detection and operational efficiency (Li et al., 2022; Xu et al., 2022). The significant effect (β = 0.753) illustrates how predictive models shift maintenance strategies from reactive to proactive, thereby reinforcing the probabilistic foundations of Reliability Theory (Kabir & Papadopoulos, 2018). At the same time, these results challenge criticisms that model interpretability and "black-box" limitations undermine trust in AI applications (Carvalho et al., 2019; Burkart & Huber, 2020). Although the study acknowledges concerns related to data quality and cybersecurity (Ucar, Karakose, & Kırımça, 2024), the strong coefficient suggests that such risks are outweighed by the practical reliability benefits. Hence, this research not only validates the theoretical claim that AI-driven diagnostics reshape reliability management but also highlights the limitations of traditional Reliability Theory, particularly in its neglect of non-technical issues such as interpretability and trustworthiness.

The results also demonstrate that Failure Pattern Detection via Machine Learning (FPDML) exerts a positive influence on system reliability (β = 0.665), confirming arguments that machine learning effectively detects hidden anomalies and anticipates failures (Mohammed et al., 2019; Wang et al., 2022). This finding reinforces the ontological premise that system failures follow identifiable patterns within data, which AI can uncover (Ucar, Karakose, & Kırımça, 2024). Nevertheless, it partly contradicts critiques emphasizing the vulnerability of FPDML to noisy or incomplete datasets that reduce accuracy (Aral & Brandić, 2021). While interpretability concerns remain valid, the overall positive impact indicates that the practical advantages of FPDML outweigh these theoretical limitations. Moreover, the evidence challenges epistemological skepticism toward data-driven knowledge, showing that iterative machine learning significantly enhances reliability in distributed environments. Accordingly, the study advances theory by affirming FPDML's predictive capacity while countering claims that its utility is severely constrained by data imperfections.

Finally, the empirical evidence confirms the moderating role of Edge Computing Integration (ECI) (β = 0.501), which strengthens the relationship between predictive maintenance and system reliability. This result aligns with the principles of Edge AI and Distributed System Reliability, which emphasize latency reduction and fault tolerance in decentralized systems (Sun et al., 2020; Yu et al., 2022). The findings support proponents who argue that ECI enhances real-time decision-making and reduces downtime (Bidollahkhani & Kunkel, 2024), though they diverge somewhat from critiques that highlight scalability challenges and cybersecurity vulnerabilities in edge environments (Artiushenko et al., 2023; Ferrag et al., 2023). While such risks are acknowledged, the results indicate they do not fundamentally diminish the moderating effect of ECI. Instead, the positive coefficient suggests that perspectives underestimating distributed architectures fail to capture their synergy with AI. Thus, this study extends existing theory by positioning ECI not as a supplementary feature but as a critical enabler of next-generation reliability in complex computing environments.

5.3. Practical implication

The findings of this study reveal several important practical implications. First, the strong positive effect of AI-based predictive maintenance on system reliability (β = 0.753) underscores its transformative potential for industries that depend on uninterrupted operations. Organizations are therefore encouraged to invest in AI-driven maintenance frameworks to minimize downtime and enhance resilience, particularly in mission-critical domains such as manufacturing, cloud computing, and industrial IoT. Prior studies (Rosati et al., 2023; Liu et al., 2021) have shown that AI-enabled real-time anomaly detection can extend equipment lifespan and reduce operational costs, indicating that firms adopting predictive maintenance will gain a competitive advantage through improved efficiency and cost savings.

Second, the significant impact of Failure Pattern Detection via Machine Learning (FPDML) on reliability (β = 0.665) highlights its value in strengthening operational performance. Companies can benefit substantially by integrating ML-driven anomaly detection into maintenance protocols, where models trained on both historical and real-time data help reduce downtime and improve reliability (Mohammed et al., 2019; Wang et al., 2022). However, the results also emphasize the necessity of robust data governance, as poor data quality diminishes predictive accuracy. Ensuring comprehensive, high-quality datasets is therefore critical to maximizing the benefits of FPDML, especially in sectors such as smart manufacturing and digital infrastructure, where reliability is directly tied to profitability.

Third, the moderating role of Edge Computing Integration (ECI) (β = 0.501) points to practical advantages for organizations operating in distributed environments. By integrating AI with edge architectures, firms can reduce latency, improve fault tolerance, and strengthen real-time responsiveness (Yu et al., 2022; Bidollahkhani & Kunkel, 2024). This finding suggests that hybrid edge–cloud strategies should be adopted to optimize reliability, particularly where connectivity to central servers is limited. At the same time, organizations must carefully address the scalability and cybersecurity risks highlighted in prior studies (Artiushenko et al., 2023; Ferrag et al., 2023). Investments in security protocols, lightweight consensus mechanisms, and energy-efficient algorithms are essential to safeguard the advantages of ECI. Overall, the evidence positions ECI not as a secondary infrastructure element but as a strategic enabler of next-generation system reliability.

5.4. Limitations

Although this study offers valuable contributions, several limitations should be acknowledged. First, the use of self-reported survey data may introduce bias, as participants' perceptions of reliability improvements do not necessarily reflect actual system performance. Second, the scope of data collection limited to three Southeast Asian countries reduces the generalizability of findings, given regional differences in infrastructure maturity and technological adoption. Third, the moderating role of edge computing was examined conceptually rather than through direct measurements of latency, bandwidth, or energy efficiency, which may influence the results. Finally, while issues such as AI model interpretability, scalability, and cybersecurity vulnerabilities were recognized, they were not empirically tested. Taken together, these limitations suggest that the findings should be viewed as indicative insights rather than conclusive evidence applicable to all computing environments.

5.5. Future Research Directions

Future studies should extend these findings through longitudinal research to examine how AI-based predictive maintenance influences system reliability over time, rather than relying solely on cross-sectional perceptions. Empirical assessments of edge computing metrics such as latency reduction, fault tolerance, and energy efficiency are needed to provide stronger evidence of its moderating role. Comparative investigations across industries and geographic regions could further evaluate the scalability of both FPDML and ECI in diverse environments. In addition, future work should address unresolved issues of model interpretability and cybersecurity by incorporating approaches such as Explainable AI (Rjoub et al., 2023) and secure edge learning protocols (Ferrag et al., 2023). Finally, mixed-method designs that integrate technical experimentation with user-centered evaluations may yield richer insights into both the technological and organizational dimensions of predictive maintenance adoption.

5.6. Conclusion

This study offers empirical evidence that AI-based predictive maintenance and machine learning–driven failure pattern detection significantly improve system reliability in computer engineering, with edge computing integration further reinforcing this effect. The findings support theoretical perspectives from Reliability Theory, Edge AI, and Distributed System Reliability, while also addressing critiques concerning data quality, interpretability, and cybersecurity. From a practical standpoint, the results encourage organizations to adopt AI-enabled diagnostics and hybrid edge–cloud strategies to reduce downtime and enhance operational efficiency. However, limitations related to measurement scope and contextual generalizability underscore the need for additional empirical validation. Overall, the study advances both theory and practice by demonstrating how AI and edge computing collectively shape the reliability of next-generation distributed systems.

REFERENCES

1. Alavian, P., Eun, Y., Liu, K., Meerkov, S.M. and Zhang, L., 2020. The (α, β)-precise estimates of MTBF and MTTR: Definition, calculation, and observation time. *IEEE Transactions on Automation Science and Engineering*, *18*(3), pp.1469-1477. https://doi.org/10.1109/tase.2020.3017134.
2. Duer, S., Woźniak, M., Paś, J., Zajkowski, K., Bernatowicz, D., Ostrowski, A. and Budniak, Z., 2023. Reliability testing of wind farm devices based on the mean time between failures (MTBF). *Energies*, *16*(4), p.1659. https://doi.org/10.3390/en16041659.
3. Farooq, M., Mir, R., Alvi, A., Tutusaus, K., Villena, E., Alrowais, F., Karamti, H., and Ashraf, I., 2025. Harnessing AI forward and backward chaining with telemetry data for enhanced diagnostics and prognostics of smart devices. Scientific Reports, 15. https://doi.org/10.1038/s41598-025-89266-9.
4. Habyarimana, M., and Adebiyi, A., 2025. A Review of Artificial Intelligence Applications in Predicting Faults in Electrical Machines. Energies. https://doi.org/10.3390/en18071616.
5. Kabir, S., and Papadopoulos, Y., 2018. A review of applications of fuzzy sets to safety and reliability engineering. Int. J. Approx. Reason., 100, pp. 29-55. https://doi.org/10.1016/j.ijar.2018.05.005.
6. Li, S., Ding, T., Mu, C., Huang, C., and Shahidehpour, M., 2022. A Machine Learning-Based Reliability Evaluation Model for Integrated Power-Gas Systems. IEEE Transactions on Power Systems, 37, pp. 2527-2537. https://doi.org/10.1109/tpwrs.2021.3125531.
7. Merenda, M., Porcaro, C., and Iero, D., 2020. Edge Machine Learning for AI-Enabled IoT Devices: A Review. Sensors (Basel, Switzerland), 20. https://doi.org/10.3390/s20092533.
8. Mittal, S. and Vetter, J.S., 2015. A survey of techniques for modeling and improving reliability of computing systems. *IEEE Transactions on Parallel and Distributed Systems*, *27*(4), pp.1226-1238. https://doi.org/10.1109/TPDS.2015.2426179.
9. Rjoub, G., Bentahar, J., Wahab, O., Mizouni, R., Song, A., Cohen, R., Otrok, H., and Mourad, A., 2023. A Survey on Explainable Artificial Intelligence for Cybersecurity. IEEE Transactions on Network and Service Management, 20, pp. 5115-5140. https://doi.org/10.1109/TNSM.2023.3282740.
10. Sarker, I., Janicke, H., Mohsin, A., Gill, A., and Maglaras, L., 2024. Explainable AI for cybersecurity automation, intelligence and trustworthiness in digital twin: Methods, taxonomy, challenges and prospects. ICT Express, 10, pp. 935-958. https://doi.org/10.1016/j.icte.2024.05.007.
11. Sun, H., Yu, H., Fan, G., and Chen, L., 2020. QoS-Aware Task Placement With Fault-Tolerance in the Edge-Cloud. IEEE Access, 8, pp. 77987-78003. https://doi.org/10.1109/ACCESS.2020.2977089.
12. Xu, Y., Kohtz, S., Boakye, J., Gardoni, P., and Wang, P., 2022. Physics-informed machine learning for reliability and systems safety applications: State of the art and challenges. Reliab. Eng. Syst. Saf., 230, pp. 108900. https://doi.org/10.1016/j.ress.2022.108900.
13. Zhang, Y., Xia, G., Yu, C., Li, H., and Li, H., 2024. Fault-Tolerant Scheduling Mechanism for Dynamic Edge Computing Scenarios Based on Graph Reinforcement Learning. Sensors (Basel, Switzerland), 24. https://doi.org/10.3390/s24216984.
14. Zio, E., 2009. Reliability engineering: Old problems and new challenges. Reliab. Eng. Syst. Saf., 94, pp. 125-141. https://doi.org/10.1016/j.ress.2008.06.002.
15. Sathupadi, K., Achar, S., Bhaskaran, S., Faruqui, N., Abdullah-Al-Wadud, M., and Uddin, J., 2024. Edge-Cloud Synergy for AI-Enhanced Sensor Network Data: A Real-Time Predictive Maintenance Framework. Sensors (Basel, Switzerland), 24. https://doi.org/10.3390/s24247918.
16. Roche, S., Bayer, Q., Carlson, B., Ouligian, W., Serhiayenka, P., Stelzer, J., and Hong, T., 2023. Nanosecond anomaly detection with decision trees and real-time application to exotic Higgs decays. Nature Communications, 15. https://doi.org/10.1038/s41467-024-47704-8.
17. Reis, M., and Serôdio, C., 2025. Edge AI for Real-Time Anomaly Detection in Smart Homes. Future Internet, 17, pp. 179. https://doi.org/10.3390/fi17040179.
18. Shi, Y., Yang, K., Jiang, T., and Letaief, K., 2020. Communication-Efficient Edge AI: Algorithms and Systems. IEEE Communications Surveys & Tutorials, 22, pp. 2167-2191. https://doi.org/10.1109/COMST.2020.3007787.
19. Shah, A., Malik, A.W., Rauf, H.T., Lali, M.I.U., Damaševičius, R. and Bouazza, D., 2022. Real-time data processing for anomaly detection: An edge computing-based AI technique. *Journal of Network and Computer Applications*, 207, p.103510. https://doi.org/10.1016/j.jnca.2022.103510.
20. Tu, J., Yang, L., and Cao, J., 2024. Distributed Machine Learning in Edge Computing: Challenges, Solutions and Future Directions. ACM Computing Surveys, 57, pp. 1 - 37. https://doi.org/10.1145/3708495.

21. Ferrag, M., Friha, O., Kantarci, B., Tihanyi, N., Cordeiro, L., Debbah, M., Hamouda, D., Al-Hawawreh, M., and Choo, K., 2023. Edge Learning for 6G-Enabled Internet of Things: A Comprehensive Survey of Vulnerabilities, Datasets, and Defenses. IEEE Communications Surveys & Tutorials, 25, pp. 2654-2713. https://doi.org/10.1109/COMST.2023.3317242.
22. Ahmed, W., and Wu, Y., 2013. A survey on reliability in distributed systems. J. Comput. Syst. Sci., 79, pp. 1243-1255. https://doi.org/10.1016/j.jcss.2013.02.006.
23. Elbamby, M., Perfecto, C., Liu, C., Park, J., Samarakoon, S., Chen, X., and Bennis, M., 2019. Wireless Edge Computing With Latency and Reliability Guarantees. Proceedings of the IEEE, 107, pp. 1717-1737. https://doi.org/10.1109/JPROC.2019.2917084.
24. Savaglio, C., Pace, P., Aloi, G., Liotta, A., and Fortino, G., 2019. Lightweight Reinforcement Learning for Energy Efficient Communications in Wireless Sensor Networks. IEEE Access, 7, pp. 29355-29364. https://doi.org/10.1109/ACCESS.2019.2902371.
25. Resende, C., Folgado, D., Oliveira, J., Franco, B., Moreira, W., Oliveira-Jr, A., Cavaleiro, A. and Carvalho, R., 2021. *TIP4.0: Industrial Internet of Things Platform for Predictive Maintenance*. Sensors, 21(14), p.4676. https://doi.org/10.3390/s21144676
26. Teoh, Y.K., Gill, S.S. and Parlikad, A.K., 2023. *IoT and Fog-Computing-Based Predictive Maintenance Model for Effective Asset Management in Industry 4.0 Using Machine Learning*. IEEE Internet of Things Journal, 10(3), pp.2087–2093. https://doi.org/10.1109/JIOT.2021.3050441.
27. Wang, X., Han, Y., Wang, C., Zhao, Q., Chen, X. and Chen, M., 2019. *In-Edge AI: Intelligentizing Mobile Edge Computing, Caching and Communication by Federated Learning*. IEEE Network, 33(5), pp.156–163. https://doi.org/10.1109/MNET.2019.1800286.
28. Ahmed, W., and Wu, Y., 2013. A survey on reliability in distributed systems. J. Comput. Syst. Sci., 79, pp. 1243-1255. https://doi.org/10.1016/j.jcss.2013.02.006.
29. Ochella, S., Shafiee, M., and Dinmohammadi, F., 2022. Artificial intelligence in prognostics and health management of engineering systems. Eng. Appl. Artif. Intell., 108, pp. 104552. https://doi.org/10.1016/j.engappai.2021.104552.
30. Mohammed, B., Awan, I., Ugail, H., and Younas, M., 2019. Failure prediction using machine learning in a virtualised HPC system and application. Cluster Computing, 22, pp. 471 - 485. https://doi.org/10.1007/s10586-019-02917-1.
31. Liu, C., Bennis, M., Debbah, M., and Poor, H., 2018. Dynamic Task Offloading and Resource Allocation for Ultra-Reliable Low-Latency Edge Computing. IEEE Transactions on Communications, 67, pp. 4132-4150. https://doi.org/10.1109/TCOMM.2019.2898573.
32. Ucar, A., Karakose, M., and Kırımça, N., 2024. Artificial Intelligence for Predictive Maintenance Applications: Key Components, Trustworthiness, and Future Trends. Applied Sciences. https://doi.org/10.3390/app14020898.
33. Stohr, A., Ollig, P., Keller, R., and Rieger, A., 2024. Generative mechanisms of AI implementation: A critical realist perspective on predictive maintenance. Inf. Organ., 34, pp. 100503. https://doi.org/10.1016/j.infoandorg.2024.100503.
34. Bouabdallaoui, Y., Lafhaj, Z., Yim, P., Ducoulombier, L., and Bennadji, B., 2021. Predictive Maintenance in Building Facilities: A Machine Learning-Based Approach. Sensors (Basel, Switzerland), 21. https://doi.org/10.3390/s21041044.
35. Çınar, Z., Nuhu, A., Zeeshan, Q., Korhan, O., Asmael, M., and Safaei, B., 2020. Machine Learning in Predictive Maintenance towards Sustainable Smart Manufacturing in Industry 4.0. Sustainability. https://doi.org/10.3390/su12198211.
36. Simion, D., Postolache, F., Fleacă, B. and Fleacă, E., 2024. *AI-Driven Predictive Maintenance in Modern Maritime Transport—Enhancing Operational Efficiency and Reliability*. Applied Sciences, 14(20), p.9439. https://doi.org/10.3390/app14209439.
37. Carvalho, D., Pereira, E., and Cardoso, J., 2019. Machine Learning Interpretability: A Survey on Methods and Metrics. Electronics. https://doi.org/10.3390/ELECTRONICS8080832.
38. Burkart, N., and Huber, M., 2020. A Survey on the Explainability of Supervised Machine Learning. ArXiv, abs/2011.07876. https://doi.org/10.1613/jair.1.12228.
39. Rosati, R., Romeo, L., Cecchini, G., Tonetto, F., Viti, P., Mancini, A. and Frontoni, E., 2023. *From Knowledge-Based to Big Data Analytic Model: A Novel IoT and Machine Learning Based Decision Support System for Predictive Maintenance in Industry 4.0*. Journal of Intelligent Manufacturing, 34, pp.107–121. https://doi.org/10.1007/s10845-022-01960-x.
40. Liu, Y., Garg, S., Nie, J., Zhang, Y., Xiong, Z., Kang, J. and Hossain, M.S., 2021. *Deep Anomaly Detection for Time-Series Data in Industrial IoT: A Communication-Efficient On-Device Federated Learning Approach*. IEEE Internet of Things Journal, 8(8), pp.6348–6359. https://doi.org/10.1109/JIOT.2020.3011726.

41. Wang, D., Zhang, C., Chen, W., Yang, H., Zhang, M., and Lau, A., 2022. A review of machine learning-based failure management in optical networks. Science China Information Sciences, 65. https://doi.org/10.1007/s11432-022-3557-9.
42. Aral, A., and Brandić, I., 2021. Learning Spatiotemporal Failure Dependencies for Resilient Edge Computing Services. IEEE Transactions on Parallel and Distributed Systems, 32, pp. 1578-1590. https://doi.org/10.1109/TPDS.2020.3046188.
43. Yu, W., Liu, Y., Dillon, T. and Rahayu, W., 2022. Edge computing-assisted IoT framework with an autoencoder for fault detection in manufacturing predictive maintenance. *IEEE Transactions on Industrial Informatics*, *19*(4), pp.5701-5710. https://doi.org/10.1109/TII.2022.3178732.
44. Mudassar, M., Zhai, Y. and Lejian, L., 2022. Adaptive Fault-Tolerant Strategy for Latency-Aware IoT Application Executing in Edge Computing Environment. IEEE Internet of Things Journal, 9, pp. 13250-13262. https://doi.org/10.1109/jiot.2022.3144026.
45. Sun, H., Yu, H., Fan, G. and Chen, L., 2020. QoS-Aware Task Placement With Fault-Tolerance in the Edge-Cloud. IEEE Access, 8, pp. 77987-78003. https://doi.org/10.1109/ACCESS.2020.2977089.
46. Bidollahkhani, M., and Kunkel, J., 2024. Revolutionizing System Reliability: The Role of AI in Predictive Maintenance Strategies. ArXiv, abs/2404.13454. https://doi.org/10.48550/arXiv.2404.13454.

Appendix: Survey

Table 6. Survey Design

Background Information						
1	In which country is your primary workplace/professional activity located?	Vietnam	Singapore	Malaysia	Other (please specify):	
2	Which professional role category best describes your field?	System Engineer / Data Scientist	IT Infrastructure / Network Administrator	Operations and Maintenance Manager	Researcher / Policy Analyst	Other (please specify):
3	Years of experience in AI-based Predictive Maintenance or related fields?	1–3 years	4–6 years	7–10 years	Over 10 years	
4	Your familiarity with Edge Computing in distributed environments?	Very low	Low	Moderate	High	Very High
5	Size of your organization?	Fewer than 50 employees	51–200 employees	201–500 employees	501–1,000 employees	More than 1,000 employees

No.	**Variables**	**Coded Sub-variables**	**Content**
1.	System Reliability in Computer Engineering (SRCE)	SRCE1	AI-based diagnostics significantly improve Mean Time Between Failures (MTBF) and reduce unplanned outages (Farooq et al., 2025; Habyarimana and Adebiyi, 2025).

		SRCE2	Real-time telemetry data combined with machine learning enhances uptime by enabling proactive maintenance actions (Xu et al., 2022).
		SRCE3	Edge computing integration improves fault tolerance, contributing to higher system reliability in distributed environments (Sun et al., 2020; Zhang et al., 2024).
		SRCE4	High system reliability strengthens operational continuity and user trust in digital infrastructure (Mittal and Vetter, 2015).
2.	AI-Based Predictive Maintenance (PM)	PM1	AI-based predictive maintenance shifts strategies from reactive to proactive, reducing downtime and extending system lifespan (Li et al., 2022; Xu et al., 2022).
		PM2	Machine learning algorithms trained on historical failure data enable timely interventions and improve reliability metrics (Kabir and Papadopoulos, 2018).
		PM3	Predictive maintenance using AI enhances maintenance efficiency by identifying anomalies early (Rosati et al., 2023; Liu et al., 2021).
		PM4	AI-driven predictive maintenance increases accuracy in fault detection compared to traditional methods (Simion et al., 2024).
3.	Failure Pattern Detection via Machine Learning (FPDML)	FPDML1	Machine learning-based failure pattern detection identifies faults before they occur, minimizing downtime (Mohammed et al., 2019).
		FPDML2	Edge-enabled FPDML enables low-latency processing for real-time failure detection (Roche et al., 2023; Reis and Serôdio, 2025).
		FPDML3	Effective FPDML depends on high-quality, comprehensive datasets to maintain accuracy (Ucar, Karakose, and Kırımça, 2024).
		FPDML4	FPDML supports proactive maintenance by analyzing both historical and live system data (Wang et al., 2022).
4.	Edge Computing Integration (ECI)	ECI1	ECI reduces latency and network dependency, enabling real-time predictive maintenance (Yu et al., 2022).
		ECI2	Deploying AI algorithms at the edge improves fault tolerance in distributed environments (Mudassar, Zhai, and Lejian, 2022; Sun et al., 2020).
		ECI3	ECI enhances the synergy between AI-based predictive maintenance and system reliability (Bidollahkhani and Kunkel, 2024).
		ECI4	ECI supports continuous asset monitoring even when disconnected from central networks (Resende et al., 2021; Teoh et al., 2023).

Survey link:
https://docs.google.com/forms/d/e/1FAIpQLSerx2NC35m-Vn7C7hqk9-bJFmKuYFtNwOeMTKgkAN_N9RNh5g/viewform?usp=dialog.