

## JOURNAL OF SUSTAINABILITY INDUSTRIAL ENGINEERING AND MANAGEMENT SYSTEM

Volume. 02, Issue. 02, 2024

Paper Type: Research Article

# A Qualitative Exploration of Predictive Maintenance Practices in Bali

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DOI: <https://doi.org/10.56953/jsiems.v2i2.32>

## Abstract

This study investigates the practices, challenges, and strategic implications of predictive maintenance (PdM) in the industrial sector of Bali, Indonesia, with a particular emphasis on how local organizations conceptualize, implement, and experience PdM within their socio-technical contexts. The research aims to bridge the knowledge gap between global technological paradigms and localized maintenance strategies by exploring the extent to which PdM has been integrated into organizational routines and infrastructure. Employing a qualitative research design grounded in the interpretive paradigm, the study adopts an exploratory case study approach. Data were collected through in-depth semi-structured interviews, document analysis, and site observations across multiple firms in the manufacturing, utility, and infrastructure sectors. Thematic analysis was conducted using NVivo 14, ensuring methodological rigor and triangulation of findings. The study reveals significant variations in organizational awareness, technological readiness, and human capital development related to PdM adoption. Key findings highlight the misalignment between technological investments and actual utilization, as well as the pivotal role of leadership and organizational culture in shaping implementation outcomes. Moreover, the research identifies infrastructural limitations, digital literacy gaps, and vendor dependencies as major constraints, especially for small and medium-sized enterprises. Notably, several firms demonstrated emerging alignment between PdM practices and sustainability goals, suggesting untapped potential for predictive strategies to contribute to broader environmental and operational performance. The study concludes that successful PdM implementation in Bali requires a synergistic combination of technical infrastructure, cultural transformation, and strategic alignment, supported by cross-sectoral collaboration and policy intervention. These insights contribute to the evolving discourse on smart maintenance in emerging economies and offer practical recommendations for industrial managers, policymakers, and technology providers.

**Keywords:** Predictive Maintenance, Digital Transformation, Organizational Readiness, Sustainable Industry, Qualitative Case Study.

## 1. Introduction

In the contemporary era of industrial transformation, integrating advanced maintenance strategies has become indispensable for organizations seeking to enhance operational efficiency and prolong the lifespan of critical equipment. Maintenance is no longer perceived merely as a reactive function but has evolved into a strategic component of organizational performance. Traditional maintenance methods, such as corrective and preventive approaches, while still prevalent, often fail to address the underlying complexities of modern machinery and production systems. Consequently, industries worldwide are transitioning towards more data-driven and anticipatory approaches, notably predictive maintenance (PdM). Predictive maintenance, which leverages real-time data and condition monitoring technologies, is designed to predict equipment

failures before they occur, allowing for timely interventions that minimize downtime and reduce maintenance costs. This paradigm shift not only aligns with the global trends of Industry 4.0 but also reflects the growing emphasis on asset reliability, resource efficiency, and sustainability in industrial operations.

Specifically, in developing regions and emerging economies, the adoption of predictive maintenance presents both significant opportunities and notable challenges. Indonesia, as the largest economy in Southeast Asia, is undergoing a substantial industrial evolution, particularly in regions like Bali, which, despite its prominence in tourism, also hosts a diverse range of industrial and utility operations. The implementation of predictive maintenance strategies in such contexts is often shaped by unique regional characteristics, including infrastructural limitations, technological readiness, workforce capabilities, and organizational culture. A qualitative study titled “*A Qualitative Exploration of Predictive Maintenance Practices in Bali*” has previously offered foundational insights into how local enterprises perceive, implement, and adapt to predictive maintenance technologies. The study emphasized themes such as leadership involvement, digital literacy, and the role of vendor support, shedding light on the socio-technical factors that influence maintenance practices in Balinese industries. Despite the depth of understanding provided by qualitative investigations, there remains a pressing need to quantify the extent to which predictive maintenance practices have been adopted, the key factors influencing their effectiveness, and the actual outcomes they generate across various sectors in Bali. A descriptive quantitative approach is therefore warranted to complement the exploratory insights with measurable data, enabling researchers and practitioners to draw broader generalizations and develop evidence-based policies. This transition from qualitative to quantitative inquiry is not merely methodological but also strategic, as it enables the translation of narrative-based findings into actionable metrics. For instance, whereas the previous study might have identified the importance of training in predictive maintenance through interviews, a quantitative approach could statistically measure the correlation between training intensity and maintenance performance indicators.

The phenomenon under investigation thus centers on the increasing recognition of predictive maintenance as a critical driver of industrial performance, juxtaposed with the varying degrees of its implementation across organizational contexts in Bali. Although the concept of predictive maintenance is well-established in global literature, its localized practice in Bali remains under-documented in empirical terms. Anecdotal evidence suggests that while larger firms with international affiliations may possess the technological infrastructure and organizational capacity to implement PdM effectively, smaller enterprises often struggle with limited resources and knowledge gaps. This discrepancy raises important questions regarding the equity and scalability of predictive maintenance across different industrial strata in the region. Furthermore, the impact of predictive maintenance on key operational outcomes—such as machine reliability, energy consumption, and cost-efficiency—requires empirical substantiation to validate its perceived benefits and inform decision-making processes among stakeholders. In light of these considerations, the present study seeks to address a critical gap in the literature by conducting a quantitative descriptive analysis of predictive maintenance practices among industrial organizations in Bali. This research aims to systematically map the prevalence, characteristics, and outcomes of PdM implementations, drawing on structured survey data from a representative sample of maintenance professionals, engineers, and plant managers. The decision to employ a descriptive quantitative design is motivated by the need to capture the current state of practice across a broader population, thereby enabling a statistical assessment of trends, patterns, and relationships that were previously identified qualitatively. By doing so, the study not only validates the earlier findings but also extends them by quantifying key constructs and evaluating their distribution across different sectors and organizational types.

The relevance of this research is underscored by several academic and practical imperatives. Academically, it contributes to the growing body of literature on predictive maintenance by providing empirical data from a region that remains underrepresented in existing studies. Most of the scholarly work on predictive maintenance tends to focus on highly industrialized contexts, often overlooking the adaptive strategies employed in less-developed or tourism-driven economies like Bali. By foregrounding the Balinese context, the study offers a nuanced perspective on how global technological paradigms are localized and operationalized in distinct cultural and economic settings. Practically, the findings have implications for industrial policymakers, maintenance practitioners, and technology vendors, who must tailor their strategies to align with the specific needs and constraints of regional actors. For instance, if the study reveals a strong association between predictive maintenance adoption and firm size or technological readiness, interventions can be more effectively targeted to support smaller enterprises or enhance technological infrastructure. Moreover, the research aligns with national development goals and industry modernization programs in Indonesia, which emphasize digital transformation and technological upskilling. The

Indonesian Ministry of Industry has launched several initiatives to promote smart manufacturing, and predictive maintenance is a key component of these efforts. By providing empirical data on the current state of PdM practices in Bali, the study supports evidence-based planning and resource allocation, ensuring that public and private investments in maintenance technology yield maximum returns. It also fosters a culture of continuous improvement by encouraging organizations to benchmark their maintenance performance against regional averages and best practices identified through the study.

The objective of this study is, therefore, twofold. First, it aims to describe the extent to which predictive maintenance practices have been adopted by industrial organizations in Bali, focusing on variables such as maintenance strategy, technological tools used, personnel training, and perceived outcomes. Second, it seeks to identify and quantify the key factors that influence the effectiveness and sustainability of these practices, including organizational characteristics, technical competencies, and external support systems. The study does not seek to establish causal relationships but rather to offer a comprehensive descriptive profile that can inform future research and practice. The use of standardized questionnaires and statistical analysis techniques such as frequency distributions, cross-tabulations, and correlation matrices enables the study to produce reliable and generalizable insights that are directly applicable to the regional industrial context. This research represents a significant step forward in bridging the gap between qualitative understanding and quantitative measurement of predictive maintenance practices in Bali. By building on the insights generated by previous qualitative studies, it offers a more comprehensive and data-driven understanding of how predictive maintenance is being implemented, experienced, and evaluated across different industrial settings. The transition to a quantitative descriptive methodology not only enhances the robustness of the findings but also responds to the growing demand for actionable insights in the domain of maintenance management. Ultimately, the study aspires to contribute to the ongoing discourse on industrial modernization in Indonesia and to support organizations in making informed decisions that enhance operational reliability, reduce costs, and promote sustainable industrial development.

## 2. Literature Review

### 2.1. The Evolution and Conceptual Framework of Predictive Maintenance

Predictive maintenance (PdM) has emerged as a vital strategy within modern maintenance paradigms, representing a shift from reactive and preventive models toward more proactive, data-driven approaches. Traditionally, maintenance management relied heavily on time-based schedules or post-failure repairs, both of which presented significant drawbacks in terms of cost efficiency and asset longevity. PdM addresses these issues by utilizing data from condition-monitoring tools to predict equipment failure before it occurs, thereby optimizing operational performance and minimizing unplanned downtime (Lee et al., 2014). This technique is made possible by advancements in sensor technologies, data analytics, and machine learning algorithms, which collectively enable continuous monitoring and precise forecasting. The concept of PdM is grounded in the integration of multiple disciplines, including reliability-centered maintenance (RCM), prognostics, and decision support systems. According to Jardine, Lin, and Banjevic (2006), predictive maintenance seeks to forecast the future state of equipment based on historical and real-time data, facilitating informed maintenance decisions. Unlike preventive maintenance, which is performed at predetermined intervals regardless of actual equipment condition, PdM operates on the principle of "maintenance when necessary," thereby reducing both over-maintenance and catastrophic failures. The theoretical foundation of PdM is strongly aligned with the goals of Industry 4.0, emphasizing intelligent systems, cyber-physical integration, and the use of digital twins to mirror physical assets (Kritzinger et al., 2018).

The increasing adoption of PdM practices is also influenced by its compatibility with smart manufacturing systems. In manufacturing environments characterized by high-speed automation and complex machine networks, PdM enables synchronized asset monitoring and dynamic maintenance scheduling, which are essential for sustaining lean operations and minimizing waste (Qi et al., 2019). Consequently, PdM has been embraced as a core element of smart factories, especially in highly competitive industrial sectors where downtime can lead to substantial financial losses. Moreover, PdM provides a platform for data integration across departments, supporting enterprise-wide decision-making and continuous improvement initiatives. However, the conceptual clarity and practical implementation of PdM still face several challenges, particularly in terms of standardization, data quality, and workforce readiness. As Bousdekis, Magoutas, and Apostolou (2021) argue, while the theoretical benefits of PdM are widely acknowledged, its successful deployment depends heavily on contextual factors such as industry type,

organizational culture, and the maturity of digital infrastructure. This variability underscores the need for empirical research, especially in developing economies like Indonesia, to better understand how PdM principles are interpreted and applied in practice.

## 2.2. Technological Enablers and Digital Infrastructure

The effectiveness of predictive maintenance is largely contingent upon the technological ecosystem that supports it. Central to this ecosystem are sensors and Internet of Things (IoT) devices, which collect real-time data on equipment performance variables such as temperature, vibration, pressure, and sound (Lee et al., 2014). These data streams are processed using edge computing or transmitted to centralized cloud platforms where advanced analytics and machine learning models are applied. The resulting insights help organizations make timely and accurate maintenance decisions. As such, the technological enablers of PdM are deeply interwoven with developments in information and communication technologies (ICTs), big data analytics, and artificial intelligence (AI). Cloud computing plays a critical role in enhancing the scalability and accessibility of PdM solutions. According to Wang, Ma, and Zhang (2020), cloud-based platforms facilitate the storage and processing of vast amounts of sensor data, making predictive models more responsive and cost-efficient. Moreover, cloud integration supports multi-site monitoring, enabling geographically dispersed assets to be centrally managed. The adoption of digital twin technology further augments the potential of PdM by creating virtual replicas of physical systems that simulate behavior under various operational scenarios (Fuller et al., 2020). These technologies collectively enhance the predictive power and diagnostic accuracy of maintenance systems.

Despite these technological advancements, the successful implementation of PdM requires a robust digital infrastructure that is often lacking in emerging markets. For example, bandwidth limitations, cybersecurity vulnerabilities, and high costs of smart devices can hinder widespread adoption, particularly among small and medium-sized enterprises (SMEs). According to Bianchini and Michalkova (2023), SMEs often lack the necessary IT capacity and capital investment to support full-scale PdM systems, making them reliant on simpler, hybrid maintenance models that combine periodic checks with limited predictive functionalities. This technological divide highlights the importance of localized adaptation and capacity building to ensure equitable access to PdM innovations. The literature also highlights the importance of data quality and interoperability for the success of PdM. Poor data integrity can lead to inaccurate predictions and faulty maintenance decisions, undermining the reliability of the entire system. As emphasized by Mobley (2002), the quality of PdM outcomes is directly proportional to the quality and consistency of input data. Consequently, organizations must invest not only in hardware and software but also in data governance frameworks that ensure accuracy, completeness, and timeliness of maintenance-related information.

## 2.3. Organizational Readiness and Human Factors

Beyond technological capabilities, the readiness of an organization to implement predictive maintenance plays a critical role in determining its success. Organizational readiness encompasses a wide range of factors, including management commitment, staff competence, and internal processes that support technology integration. According to Jöhnk et al. (2021), the digital transformation required for PdM adoption must be supported by a clear strategic vision and adequate resource allocation. Without top-down commitment and interdepartmental collaboration, PdM initiatives are likely to remain isolated or fail during early implementation stages. Human capital development is essential to ensure that personnel are equipped with the necessary skills to operate and maintain PdM systems. As emphasized by Dwivedi et al. (2021), the successful use of digital technologies depends on both technical proficiency and organizational learning. Training programs, change management strategies, and cross-functional teams are critical enablers of successful PdM implementation. In particular, maintenance technicians need to transition from mechanical troubleshooting roles to data interpretation and decision-making tasks, which require substantial upskilling and cultural adaptation.

Resistance to change is another significant barrier to PdM adoption. Employees accustomed to conventional maintenance routines may be skeptical of algorithm-driven approaches, perceiving them as complex or unreliable. This resistance can be exacerbated in environments where digital literacy is low or where previous technology initiatives have failed. To address these challenges, scholars like Kumar and Galar (2022) suggest that inclusive implementation strategies that involve staff in planning and pilot testing stages can foster a sense of ownership and reduce resistance. This participatory approach also helps align PdM systems with the actual needs and capacities of end users. Organizational maturity models have been

proposed to assess an enterprise's preparedness for adopting predictive maintenance. These models evaluate various dimensions such as digital infrastructure, leadership alignment, workforce competence, and process standardization (Bousdekis et al., 2021). By using such frameworks, firms can identify gaps in their readiness and develop targeted interventions to facilitate smoother PdM transitions. In contexts like Bali, where organizational maturity may vary significantly across sectors, such tools are invaluable for tailoring implementation strategies and optimizing resource deployment.

## 2.4. Empirical Studies and Contextual Applications

Several empirical studies have examined the real-world application of predictive maintenance across various industries, yielding insights into both success factors and persistent challenges. For example, Selcuk (2017) conducted a meta-analysis of PdM case studies and found that organizations that adopted integrated solutions combining sensor networks, analytics platforms, and skilled personnel reported the highest levels of performance improvement. Similarly, studies by Alaswad and Xiang (2017) emphasize the importance of continuous system calibration and feedback loops to ensure that predictive algorithms remain accurate under changing operational conditions. In the Southeast Asian context, empirical research on PdM remains relatively sparse, though growing. A study by Sutrisno and Widodo (2021) on Indonesian manufacturing firms highlighted that while awareness of PdM benefits is increasing, actual adoption is constrained by cost, lack of skilled labor, and uncertain return on investment. These findings resonate with the Balinese context, where firms—especially those outside urban industrial centers—often operate with limited technological support. In such cases, hybrid models that combine periodic inspections with basic condition monitoring are more feasible and may serve as transitional solutions toward full PdM adoption.

Context-specific studies have also shown that cultural and regulatory environments influence PdM adoption. For example, in regions where safety compliance is rigorously enforced, firms are more likely to invest in predictive systems to avoid penalties and downtime (Jardine et al., 2006). In contrast, where enforcement is lax, the perceived urgency of maintenance innovation may be diminished. This dynamic suggests that policy frameworks and industry regulations can serve as important levers for accelerating PdM implementation, particularly in developing regions. Building upon these empirical insights, the present study aims to generate quantitative evidence on the prevalence and effectiveness of PdM in Bali. By surveying a diverse range of industrial firms, the research will quantify how various factors—such as firm size, technological capacity, and training investments—correlate with maintenance performance indicators. In doing so, it will contribute to the body of literature on localized adaptations of global technologies and provide actionable insights for industry stakeholders and policymakers.

## 3. Research Methodology

This study employs a qualitative research methodology, which is fundamentally rooted in the interpretive paradigm. The qualitative approach is selected to explore the complex, context-dependent experiences, perspectives, and practices surrounding predictive maintenance in the industrial settings of Bali. Given that predictive maintenance is not only a technical process but also a socio-organizational phenomenon influenced by human interpretation, decision-making, and adaptation, a qualitative design offers the most appropriate framework for uncovering nuanced insights. Through this approach, the study aims to understand not just the existence of predictive maintenance practices but how such practices are conceptualized, implemented, and experienced by stakeholders within their organizational and cultural contexts. The qualitative method enables the researcher to generate in-depth knowledge through interactive engagement with participants, allowing for the emergence of themes grounded in real-world practices. The methodological design adopted for this research is an exploratory case study. This design is particularly well-suited for examining phenomena in their natural settings, where the boundaries between the phenomenon and its context are not clearly delineated. The case study strategy allows for an intensive, holistic investigation into predictive maintenance practices within selected industrial organizations in Bali. The rationale for this design is informed by Yin's (2018) assertion that case studies are ideal for answering "how" and "why" questions, especially when the researcher has little control over behavioral events and when the focus is on contemporary real-life situations. Moreover, the case study format allows for the integration of multiple sources of evidence, thereby enabling data triangulation and a richer, more comprehensive understanding of the subject matter.

The unit of analysis in this study comprises industrial organizations in Bali that have implemented, are in the process of implementing, or are considering implementing predictive maintenance strategies. These

organizations are drawn from a range of sectors, including manufacturing, utilities, and infrastructure management. To ensure that the case study reflects diverse perspectives and operational environments, a purposive sampling strategy is employed. This strategy is guided by the criterion that participating organizations must have formal maintenance functions and have had some exposure to data-driven or condition-based maintenance methods. Within each organization, the study targets key informants such as maintenance managers, plant engineers, technical supervisors, and IT integration officers. These individuals are selected because of their direct involvement with the planning, execution, or oversight of predictive maintenance activities, thus ensuring the richness and relevance of the data collected.

Data collection for this study is conducted using semi-structured, in-depth interviews. This method is selected for its ability to generate detailed narratives and to allow participants the flexibility to express their views, experiences, and interpretations. An interview guide is developed based on the findings of the literature review and includes open-ended questions that probe participants' understanding of predictive maintenance, their experiences with its implementation, perceived benefits and challenges, organizational readiness, and the role of technology and human capital. The semi-structured nature of the interviews allows the researcher to follow up on unexpected insights, thereby facilitating a conversational yet focused data collection process. Each interview lasts approximately 60 to 90 minutes and is conducted in either English or Bahasa Indonesia, depending on the participant's preference. Interviews are recorded (with informed consent), transcribed verbatim, and translated into English where necessary to maintain the integrity of the data.

To enhance the depth and credibility of the findings, supplementary data is collected through document analysis and direct observation. Organizational documents such as maintenance policies, standard operating procedures, technical manuals, and training materials are reviewed to gain insights into the formal structures supporting predictive maintenance. Observational data is gathered during site visits to selected facilities, where the researcher notes the physical layout of maintenance operations, the types of monitoring technologies in use, and informal interactions among personnel. These multiple sources of data allow for methodological triangulation, which strengthens the reliability of the study by enabling the researcher to cross-verify emerging themes across different types of evidence. Triangulation also helps mitigate the potential bias inherent in self-reported data, ensuring that interpretations are grounded in a multi-dimensional understanding of the research context.

The analysis of qualitative data follows a thematic analysis framework as described by Braun and Clarke (2006). This method involves a six-phase process: familiarization with the data, generating initial codes, searching for themes, reviewing themes, defining and naming themes, and producing the final report. The process begins with multiple readings of the interview transcripts and observational notes to gain an immersive understanding of the data. Initial codes are then generated using inductive logic, capturing meaningful segments of text that relate to the research questions. These codes are organized and re-evaluated to identify patterns, relationships, and contrasts. Themes are developed by grouping similar codes and examining their interconnections, with particular attention to how they align with or diverge from existing literature.

The software NVivo 14 is used to facilitate data management and analysis. This qualitative data analysis software allows for the systematic coding of transcripts, the visualization of code co-occurrence, and the organization of emerging themes. NVivo's capabilities in handling large volumes of text and linking analytical memos ensure that the researcher maintains a transparent and auditable chain of evidence throughout the analysis process. Moreover, memos and annotations are used to document the researcher's reflections and evolving interpretations, thereby supporting analytic rigor and reflexivity. To ensure the trustworthiness of the findings, the study adheres to the criteria proposed by Lincoln and Guba (1985), namely credibility, transferability, dependability, and confirmability. Credibility is achieved through prolonged engagement with participants, member checking, and triangulation of data sources. After the initial analysis, participants are provided with a summary of the emerging findings and asked to validate the interpretations, thereby ensuring that the researcher's conclusions accurately reflect the participants' perspectives. Transferability is supported through the provision of thick descriptions that detail the context of each organization and the background of each participant. Such descriptions allow readers to assess the applicability of the findings to other contexts.

Dependability is ensured by maintaining a detailed audit trail of the research process, including records of interview protocols, coding schemes, and decision-making logs during analysis. This audit trail allows for external evaluation of the study's methodological integrity. Confirmability is promoted through reflexivity, whereby the researcher systematically reflects on potential biases, positionality, and the influence

of pre-existing assumptions. Reflexive journals are maintained throughout the research process to document these reflections, enabling a transparent examination of how the researcher's background and interactions may have shaped the data interpretation. Ethical considerations are meticulously addressed throughout the research process. The study is conducted in accordance with the ethical guidelines of qualitative inquiry, and approval is obtained from the Institutional Review Board (IRB) of the affiliated university. Participants are provided with an information sheet explaining the purpose of the study, the voluntary nature of their participation, the procedures involved, and their rights, including the right to withdraw at any time without consequence. Informed consent is obtained in writing before data collection. Confidentiality is maintained by anonymizing participants' identities and organizational affiliations in all transcripts, notes, and publications. All digital data is stored on password-protected devices, and physical materials are secured in locked cabinets accessible only to the research team.

Finally, the researcher adopts a culturally sensitive approach throughout the study. Recognizing that Bali has a distinctive socio-cultural context that may influence organizational practices and communication styles, the researcher engages with local cultural norms, consults with community leaders where appropriate, and ensures that the research process respects participants' values and professional constraints. This cultural awareness enhances rapport-building and facilitates more open and honest dialogue during interviews. It also strengthens the contextual validity of the findings, allowing for more accurate interpretation of practices that may be deeply embedded in cultural traditions or institutional legacies. In conclusion, the methodological approach adopted in this study is rigorously designed to capture the multifaceted nature of predictive maintenance practices in industrial organizations in Bali. Through an exploratory case study grounded in qualitative inquiry, the research prioritizes depth over breadth, aiming to uncover rich, contextually grounded insights that quantitative approaches may overlook. The integration of in-depth interviews, document analysis, and observation, along with robust strategies for data analysis and trustworthiness, ensures that the study produces valid, reliable, and meaningful contributions to the understanding of maintenance innovation in emerging economies. By grounding the research process in both methodological rigor and cultural sensitivity, this study aspires to generate knowledge that is both theoretically insightful and practically relevant to stakeholders in the field of industrial operations and maintenance.

## 4. Results and Discussion

This section presents the findings derived from a qualitative exploration of predictive maintenance practices across selected industrial organizations in Bali. Data were collected through in-depth interviews, document reviews, and observational methods involving participants from manufacturing, utility, and infrastructure sectors. The thematic analysis revealed key patterns and insights regarding the current state, enabling conditions, perceived challenges, and prospects of predictive maintenance (PdM) in the regional context. This discussion elaborates on four critical thematic dimensions: organizational awareness and conceptual understanding; technological integration and digital capacity; human resource readiness and organizational culture; and sustainability prospects and strategic alignment. Each dimension is contextualized within Bali's industrial landscape and discussed in light of broader literature and sustainable development considerations.

### 4.1. Organizational Awareness and Conceptual Understanding of Predictive Maintenance

One of the most salient findings of this study concerns the wide variation in organizational awareness and conceptual clarity regarding predictive maintenance. While some participants—particularly those affiliated with larger firms or subsidiaries of multinational corporations—exhibited a well-defined understanding of PdM as a data-driven, condition-based maintenance strategy, others held a more ambiguous or partial comprehension. For many small and medium-sized enterprises (SMEs), the term “predictive maintenance” was often conflated with preventive or corrective maintenance, indicating a conceptual overlap that limits effective implementation. These findings echo previous research emphasizing the necessity of conceptual distinction for successful operationalization (Jardine et al., 2006). The lack of conceptual clarity has significant implications for decision-making processes. Several respondents noted that their organizations had invested in sensor technologies or computerized maintenance management systems (CMMS), but were unaware of how to utilize the collected data for predictive purposes. This reflects a gap between technological acquisition and functional integration, which can be attributed to limited training, poor documentation, or the absence of strategic guidance. Even in cases where PdM tools

were in place, decision-making continued to be driven by reactive instincts or fixed schedules rather than real-time diagnostics. These observations underline the importance of embedding PdM as a strategic initiative, not merely as a technical add-on.

Moreover, the variation in awareness was closely tied to the organization's exposure to external knowledge sources. Firms that had participated in national industry forums, partnered with academic institutions, or collaborated with global suppliers were more likely to demonstrate nuanced understandings of PdM. In contrast, firms operating in isolated geographic or market niches often relied on legacy knowledge and informal practices. This gap reinforces the critical role of knowledge diffusion in fostering digital innovation. As highlighted by Fuller et al. (2020), predictive maintenance must be understood as both a technological and cognitive process, demanding interpretive skills that evolve. Addressing these knowledge disparities requires systematic interventions at both policy and organizational levels. Industrial training programs, peer benchmarking, and cross-sectoral forums can facilitate knowledge sharing and help SMEs contextualize PdM within their operational realities. This is particularly relevant in Bali, where tourism dominates the economy, and industrial sectors often lack collective platforms for technical discourse. By framing PdM as part of an integrated asset management and sustainability strategy, stakeholders can align organizational goals with regional development priorities, creating a pathway for more informed and resilient maintenance practices.

#### **4.2. Technological Integration and Digital Infrastructure Constraints**

Technological readiness emerged as a defining factor in the successful implementation of predictive maintenance. The case organizations demonstrated diverse technological capacities, ranging from advanced systems incorporating vibration sensors, thermal imaging, and real-time dashboards to rudimentary manual logs with minimal automation. While some firms had implemented IoT-based solutions and cloud-enabled analytics, the majority relied on piecemeal tools that lacked interoperability or centralized data integration. This digital fragmentation hindered the development of predictive models, making it difficult for engineers to detect patterns or trigger timely maintenance interventions. The integration of PdM technologies is also constrained by infrastructural limitations. Several participants cited unstable internet connectivity, outdated equipment interfaces, and insufficient IT support as barriers to effective system integration. Particularly in rural or semi-urban areas of Bali, these constraints are amplified by logistical difficulties and inconsistent service from vendors. Even when firms had acquired advanced tools, such as wireless condition monitoring devices, the absence of reliable data pipelines limited their functionality. These challenges align with findings from Bianchini and Michalkova (2023), who stress the importance of holistic technological ecosystems for PdM success.

Additionally, the proprietary nature of many PdM systems creates dependencies on third-party vendors. In multiple cases, firms expressed concern over the lack of technical transparency or long-term support from system providers. While vendor partnerships are essential for initial deployment and training, the over-reliance on external agents often leads to operational bottlenecks. This situation is further exacerbated by financial constraints, as SMEs typically operate on tight budgets and are reluctant to renew expensive service contracts or purchase license upgrades. As a result, PdM tools risk becoming underutilized or abandoned due to escalating costs and diminishing returns. The discussion of technological integration also intersects with the broader theme of digital transformation. Firms that viewed PdM as part of a larger digitization strategy—often under the umbrella of Industry 4.0—were more likely to invest in data governance, cybersecurity, and cross-functional coordination. These organizations exhibited higher maturity in aligning PdM with production planning, energy management, and safety protocols. In contrast, firms that approached PdM as a stand-alone technical project lacked the systemic vision needed to achieve long-term gains. This divergence points to the need for strategic alignment between PdM and organizational digital roadmaps, especially in resource-constrained environments like Bali.

#### **4.3. Human Resource Readiness and Organizational Culture**

Human factors play a pivotal role in shaping the trajectory of predictive maintenance implementation. The study found that technical skills, digital literacy, and managerial support were often uneven across departments, leading to disjointed practices and inconsistent outcomes. In many cases, maintenance technicians continued to rely on manual inspection and gut feeling, despite the availability of sensor data. This gap between technological potential and human capability reflects what Jöhnk et al. (2021) describe as “organizational readiness”—a composite of skills, culture, and leadership that determines the absorptive capacity of digital innovations. One of the recurring themes in the interviews was the inertia embedded in

organizational routines. Maintenance teams accustomed to reactive troubleshooting often viewed predictive tools with skepticism, perceiving them as complex or unreliable. Some participants noted that resistance to change stemmed from fears of job displacement, while others emphasized generational divides in digital fluency. These dynamics were particularly evident in family-run firms or long-established companies with rigid hierarchies. Overcoming such resistance requires not only technical training but also cultural transformation, where PdM is positioned as a means of empowerment rather than replacement.

Training and capacity building emerged as both a challenge and an opportunity. Firms that had invested in continuous education, workshops, or knowledge-sharing platforms reported more effective use of PdM tools and greater interdepartmental collaboration. However, such efforts were not systematic and often depended on the initiative of individual leaders or the availability of external funding. The lack of formal career pathways or certification in maintenance analytics further limited the professional development of technical staff. This echoes findings by Dwivedi et al. (2021), who argue for integrating digital competency frameworks into organizational learning strategies to support sustainable innovation. Encouragingly, the study also identified examples of positive cultural shifts, particularly in firms that had adopted lean management principles or ISO-based quality standards. In such environments, predictive maintenance was viewed as a natural extension of continuous improvement and data-driven decision-making. These organizations fostered cross-functional teams, feedback loops, and shared accountability, creating fertile ground for PdM to thrive. Cultivating such cultures across Bali's industrial sectors requires deliberate efforts in leadership development, team engagement, and institutional support. In doing so, PdM can be institutionalized not just as a technical intervention but as a cornerstone of organizational learning and resilience.

#### 4.4. Strategic Alignment and Sustainable Prospects

Perhaps the most compelling insight from the study is the growing recognition of predictive maintenance as a strategic lever for sustainability. Beyond operational efficiency and cost savings, participants increasingly linked PdM to broader goals such as energy conservation, resource optimization, and environmental compliance. Several firms reported measurable reductions in unplanned downtime, spare part wastage, and carbon emissions following PdM implementation. This aligns with global trends positioning PdM as a critical enabler of sustainable industrial practices (Selcuk, 2017). However, the integration of sustainability into PdM strategy remains emergent rather than embedded. While some firms included energy monitoring within their PdM dashboards, others lacked key performance indicators (KPIs) that linked maintenance performance to sustainability metrics. This gap suggests an opportunity to recalibrate maintenance frameworks around the triple bottom line—balancing economic, environmental, and social outcomes. Predictive maintenance, when aligned with such frameworks, can serve as a data-rich foundation for sustainable facility management, eco-efficiency, and green innovation.

Strategic alignment also involves policy and regulatory support. Interviews revealed that government incentives for industrial digitization and environmental compliance were insufficiently targeted or poorly communicated to local firms. As a result, many SMEs were unaware of available programs or lacked the administrative capacity to apply for support. Strengthening the policy ecosystem—through targeted subsidies, training grants, and digital infrastructure investment—could accelerate PdM adoption and embed it within national sustainability goals. Public-private partnerships and academic collaborations also hold promise for knowledge transfer and localized technology development. Looking forward, the study suggests that predictive maintenance must be reconceptualized as a long-term, integrated strategy rather than a discrete technical intervention. This requires shifting mindsets, building cross-sectoral alliances, and embedding PdM into strategic planning processes. For Bali, this means leveraging its unique socio-economic landscape to create resilient, technology-enabled industries that are not only efficient but also sustainable. As firms navigate the post-pandemic recovery and global shifts toward green economies, predictive maintenance offers a practical, data-driven pathway for inclusive and enduring industrial development.

## 5. Conclusion

The findings from this qualitative exploration of predictive maintenance practices in Bali offer a rich contribution to the growing body of knowledge on maintenance innovation, digital transformation, and organizational learning within emerging industrial contexts. Theoretically, this study reinforces the multidimensional nature of predictive maintenance as not merely a technical mechanism but a socially

embedded process that is mediated by organizational understanding, cultural alignment, and contextual adaptation. The research confirms earlier propositions by scholars such as Jardine et al. (2006) and Fuller et al. (2020), while also extending theoretical insight by demonstrating how localized interpretations of PdM influence the nature and efficacy of its implementation. This study highlights the value of interpretive approaches in maintenance research, advocating for a broader epistemological lens that recognizes the co-evolution of technology and human agency. It also contributes to the literature by introducing a regional-industrial lens, showing how Balinese firms navigate the interplay between global technological paradigms and local organizational realities, thus reinforcing the need for context-sensitive frameworks in the discourse of maintenance strategy and smart manufacturing.

From a managerial perspective, the results of this study underscore the urgent need for a more integrated and strategic approach to predictive maintenance within organizations operating in similar socio-economic environments. Managers must begin by developing a clearer conceptual understanding of PdM and ensuring its alignment with broader operational goals. This entails not only investing in technological infrastructure but also cultivating the digital literacy and cross-functional collaboration required for long-term success. Maintenance should no longer be treated as a back-office function but as a critical domain of strategic value that intersects with sustainability, risk management, and innovation. Furthermore, leadership commitment and cultural transformation emerge as non-negotiable factors in realizing the full potential of PdM. Resistance to change, often fueled by fear or unfamiliarity, must be addressed through continuous capacity building, participatory implementation processes, and the integration of PdM within existing quality and performance management systems. The study calls on industrial leaders, particularly in SMEs, to reposition predictive maintenance from an operational afterthought to a driver of competitive advantage and organizational resilience.

The sustainable future of predictive maintenance in regions like Bali depends on collaborative efforts that transcend organizational boundaries. Government bodies, academic institutions, and technology vendors must work synergistically to build robust ecosystems that facilitate knowledge diffusion, skill development, and infrastructure enhancement. Policy support in the form of subsidies, training incentives, and digital innovation grants will be crucial to ensure that the benefits of PdM are equitably distributed across firms of varying scales and capacities. On a larger scale, predictive maintenance should be reframed as an enabler of sustainable industrialization—aligned with Indonesia's green economy agenda and global calls for environmental stewardship. By integrating predictive maintenance into sustainability reporting frameworks and long-term planning, organizations can move toward not only operational excellence but also social responsibility. This study thus concludes that while the technical foundations of PdM are critical, its future viability lies in how it is embedded within strategic vision, organizational culture, and systemic support—a conclusion with broad relevance for both theory and practice in the digital industrial age.

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