# Beyond the Screen: Understanding How Predictive Dashboards Shape and Reflect Industrial Work

Investigating the Role of Predictive Maintenance Dashboards in Everyday Industrial Decision-Making

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**Abstract:**

This thesis critically investigates the adoption and interpretation of predictive maintenance (PdM) dashboards within industrial environments, integrating insights from Human–Computer Interaction (HCI), Technology Acceptance Model 2 (TAM2), and the TPOM framework. Drawing on document analysis and user survey data, the study examines how dashboard usability, social dynamics, and organizational structures influence technology uptake. Using Braun and Clarke's thematic analysis, the research identifies key themes such as cross-context usability, perceived usefulness, and organizational embedding. Findings reveal that even well-engineered dashboards face resistance or misinterpretation when they are misaligned with user cognition, workplace routines, or institutional culture. By situating PdM dashboards as techno-anthropological artifacts, the study offers practical recommendations for designing more inclusive, interpretable, and adaptive digital tools. This work contributes to the growing discourse on human-centered industrial analytics and highlights the socio-technical conditions necessary for meaningful digital transformation.

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**Keywords:** Technoanthropology, Usability, Integration, Adoption, Contextualization, Mediation

# Chapter 1: Introduction

In today's rapidly evolving industrial landscape, predictive maintenance (PdM) plays a critical role in how organizations manage equipment performance and avoid costly downtime. PdM systems use real-time data from sensors combined with algorithms and machine learning to anticipate when machines may fail, allowing repairs to be scheduled before breakdowns occur[3]. These technologies are fundamental to the evolution of Industry 4.0, which promotes digital transformation through automation, smart systems, and interconnected processes[10]. As companies continue to integrate cyber-physical systems and AI into operations, PdM dashboards are becoming standard tools in decision-making processes on the factory floor.

However, even the most sophisticated PdM algorithms are only effective when their outputs are understood and acted upon by human users. Maintenance engineers and operators rely on dashboards to provide clear, timely, and actionable insights. When these interfaces are poorly designed—overloaded with information, difficult to navigate, or culturally insensitive—critical warnings may be misinterpreted or ignored[13]. This disconnect between technical systems and human understanding can result in inefficiencies or even serious safety incidents.

Technological efficiency alone is not sufficient. How data is presented, how it fits into daily work routines, and how well users trust and comprehend predictive outputs are equally important. The ability to interpret dashboard alerts depends not only on user training but also on cognitive load, social influence, organizational culture, and broader systemic factors[8]. In this context, examining the usability and adoption of PdM dashboards requires more than technical analysis—it demands a human-centered, socio-technical perspective.

## 1.1 Industry 4.0 and Predictive Maintenance

### Industry 4.0

Industry 4.0, also referred to as the Fourth Industrial Revolution, represents a major shift in how manufacturing and production systems operate. It is characterized by the integration of cyber-physical systems, the Internet of Things (IoT), cloud computing, and artificial intelligence (AI) into manufacturing workflows[6]. These technologies enable machines to communicate with each other and with humans in real-time, leading to more autonomous, efficient, and adaptive production systems.

The goals of Industry 4.0 include increased operational efficiency, greater flexibility in production, and real-time responsiveness to market demands. As part of this shift, traditional reactive and time-based maintenance strategies are giving way to predictive maintenance, which aligns closely with Industry 4.0's emphasis on data-driven decision-making.

### Predictive Maintenance (PdM)

Predictive maintenance is a proactive approach that uses condition-monitoring tools and analytical techniques to detect potential equipment failures before they happen[19]. Unlike preventive maintenance, which occurs on a scheduled basis regardless of machine condition, PdM is triggered by actual machine data. It reduces unplanned downtime, extends asset life, and lowers maintenance costs.

PdM typically involves the collection of sensor data (e.g., vibration, temperature, pressure) which is processed through algorithms to predict remaining useful life (RUL) or identify anomalies. The results are displayed through dashboards, which are the main interface between the system and human operators. The usability of these dashboards is essential—if they are confusing or misaligned with user needs, their predictive power is lost.

## 1.2 Purpose and Importance

Understanding how predictive maintenance dashboards are adopted, interpreted, and integrated into industrial workflows holds both academic and practical significance. From an academic perspective, this research offers a critical contribution to the field of techno-anthropology by framing digital maintenance tools as socially and cognitively embedded artifacts, rather than as neutral or purely technical instruments. The study engages with theories from human-computer interaction, information systems, and socio-technical frameworks to deepen our understanding of how technological systems function within complex industrial ecosystems. It challenges the prevailing assumption that technical optimization alone ensures effective adoption and instead highlights the importance of human-centered factors like interface cognition, organizational routines, and social trust.

From a practical perspective, the findings are relevant for engineers, interface designers, maintenance managers, and policy makers involved in the development and deployment of PdM systems. As organizations continue to digitize their maintenance strategies under the broader framework of Industry 4.0, failures in system uptake often stem not from technological shortcomings, but from user disengagement, interface overload, or poor alignment with existing work practices. By uncovering the interplay between cognitive, social, and systemic factors, this study provides concrete insights into how predictive dashboards can be designed and implemented to enhance usability, foster trust, and support informed decision-making across diverse industrial settings.

The research thus positions itself at the intersection of theory and practice, offering a vision of predictive maintenance technologies that are not only smart and data-driven but also adaptive to the lived experiences, expectations, and limitations of their users. This contribution is intended to support more inclusive, sustainable, and effective digital transformation in industrial domains.

## 1.3 Research Objective

The overarching objective of this research is to critically investigate how predictive maintenance dashboards are adopted and utilized in industrial contexts by integrating perspectives from techno-anthropology, human-computer interaction (HCI), and socio-technical systems thinking. The study aims to move beyond a purely technical or engineering-focused view of PdM tools and instead understand them as culturally, cognitively, and organizationally situated artifacts. While dashboards serve as the main interface through which predictive maintenance insights are communicated, their adoption and effectiveness depend heavily on how well they align with the everyday practices, expectations, and constraints of the people using them.

Focus to uncover how different factors—ranging from interface design and perceived ease of use to social norms, team structures, and policy environments—interact to shape the experience of using PdM systems. Particular attention is given to how information is structured and visualized, how dashboard logic matches users' cognitive workflows, and how broader organizational and environmental conditions support or inhibit adoption.

By using an artifact-based analysis approach grounded in TAM2, TPOM, and HCI methods, the study aspires to generate deep, actionable insight into how PdM dashboards can be more effectively designed and implemented. It also aims to make a conceptual contribution to the field of techno-anthropology by highlighting the interdependence of digital infrastructure and social life in industrial settings. This objective supports the larger goal of enabling more responsible, user-aligned digital transformation processes within the Industry 4.0 paradigm. for safe, effective, and sustainable industrial automation. This research integrates cognitive, organizational, and systemic factors to evaluate how PdM systems are interpreted and applied in practice. So the only goal is to uncover social and cultural conditions that shape technological success.

All eys on a set of evaluative insights and tools that designers and industrial decision-makers can use to improve dashboard design. It contributes to broader discussions in techno-anthropology and digital transformation by illustrating how even advanced technologies can fail if they are misaligned with human behavior and institutional context.

**Research Questions**

To achieve this objective, the study addresses the following research questions:

- **Primary Question**: How do cognitive, social, and systemic factors influence the usability and adoption of predictive maintenance dashboards in industrial contexts?
- **Sub-Questions**:
  - How do interface design and information structure in PdM dashboards affect perceived ease of use and decision-making efficiency?
  - What role do social and organizational dynamics play in supporting or resisting the adoption of PdM tools?
  - In what ways do macro-environmental factors, such as vendor rela-

tions and regulatory pressures, shape the long-term use of predictive maintenance systems?

**Cognitive and Social factors**

Social factors on the acceptance and integration of PdM dashboards which includes team communication, managerial expectations, peer influence, and overall workplace culture. Technology does not exist in isolation; rather, it is introduced into an environment shaped by existing relationships and norms. By understanding how social dynamics either promote or obstruct the use of PdM systems, the research contributes to developing more realistic and user-aligned implementation strategies.

This could help to understand how these cognitive and social dynamics interact with organizational structures and macro-environmental conditions such as industry standards, regulatory frameworks, and vendor support systems. Through an artifact-based analysis grounded in TAM2, TPOM, and HCI methodologies, the study aims to generate actionable insights for the design and implementation of PdM dashboards that are usable, interpretable, and trusted. It also contributes to broader conversations in techno-anthropology by showing how everyday digital interfaces are intertwined with human systems of meaning, power, and practice.—such as perceived ease of use, clarity of information, and user trust—in shaping how maintenance staff engage with dashboard interfaces. The ability to comprehend system outputs without excessive cognitive load or ambiguity directly impacts whether users are able to make timely and accurate decisions. These cognitive aspects are vital in high-pressure environments where dashboards are expected to provide clear and actionable insights with minimal interpretation effort.

## 1.4 Thesis Structure

This thesis is structured across seven chapters, each building progressively to explore and interpret the socio-technical dynamics of predictive maintenance (PdM) dashboards through a techno-anthropological lens. The structure reflects a logical flow from context-setting and theory to empirical analysis, interpretation, and final conclusions:

- **Literature Review:** Provides a critical overview of existing research on PdM, dashboard usability, HCI, and technology adoption models. It identifies theoretical gaps and practical limitations that justify the need for a techno-anthropological investigation.
- **Contextual and Conceptual Positioning:** Situates the study in terms of complexity, organizational realities, and conceptual frameworks. It introduces key entry points such as data interpretation, role negotiation, and user resistance, and lays the groundwork for analytical orientation.
- **Methodology:** Details the methodological approach, including the rationale for using a mixed empirical base (Google Form responses and DIAP documentation). It outlines the use of thematic analysis and describes the

role of HCI, TAM2, and TPOM as interpretive frameworks. It also includes data collection strategies and ethical considerations.

- **Empirical Findings:** Presents the data thematically under the three frameworks: HCI (e.g., usability, feedback), TAM2 (e.g., perceived usefulness, social influence), and TPOM (e.g., organizational fit, macro-environment). This chapter stays descriptive, offering a structured and grounded presentation of results.
- **Discussion:** Provides an in-depth interpretation of the findings, linking empirical observations to theoretical constructs. It compares user experiences across regional and organizational settings and reflects on broader implications using a techno-anthropological lens. Limitations, challenges, and practical implications are also discussed.
- **Conclusion:** Synthesizes key insights from the entire study, highlights theoretical and practical contributions, addresses limitations, and proposes directions for future research. It positions the findings in the broader landscape of digital transformation and industrial decision-making.

Together, these chapters aim to provide a comprehensive, contextually rich, and theoretically informed understanding of how predictive maintenance dashboards are experienced, used, and embedded in industrial work practices.

## 1.5 Transition to Literature Review

The introductory chapter has established the background, relevance, and key concerns surrounding predictive maintenance dashboards in the context of Industry 4.0. It has outlined the importance of viewing PdM systems not merely as technical instruments but as socially embedded technologies shaped by cognitive, organizational, and cultural dynamics. The discussion also defined the scope and direction of the research, presenting the core research questions and theoretical grounding.

To better contextualize the chosen analytical approach and to frame the relevance of the applied theoretical models, the following chapter offers a review of the relevant literature. This review not only highlights existing findings in predictive maintenance, usability, and industrial interface design but also identifies key research gaps that this thesis seeks to address. The literature review builds a bridge between the conceptual framing and the methodological strategy by synthesizing perspectives from engineering, cognitive science, HCI, and techno-anthropology.

# Chapter 2: Literature Review

Predictive Maintenance (PdM) has emerged as one of the defining strategies of Industry 4.0, enabling companies to shift from reactive maintenance to data-driven, preemptive repairs. Rooted in cyber-physical systems and IoT, PdM combines real-time sensor monitoring with machine learning algorithms to identify early signs of equipment failure[30]. However, despite impressive algorithmic advances, the usability of PdM systems remains a challenge. Interface design, organizational fit, and user trust are increasingly cited as critical bottlenecks to adoption[13].

Research in industrial engineering has emphasized the performance benefits of PdM, such as cost savings and operational efficiency[19]. But studies in cognitive psychology, human-computer interaction, and organizational behavior reveal that even the best models are of little use if their alerts are misunderstood or disregarded[2]. Misalignment between system logic and user workflows can reduce trust, delay action, or result in serious errors. These findings suggest a need to expand the scope of PdM research to include socio-technical and human-centered perspectives.

## 2.1 Technological Foundations of Predictive Maintenance

Predictive maintenance (PdM) systems have emerged as a transformative element within the digitalization of industrial operations, offering a shift from reactive and time-based maintenance to condition-based, data-driven strategies. This transformation is underpinned by several key technological developments that enable predictive capabilities and smarter decision-making on the shop floor.

At the core of PdM is the deployment of Internet of Things (IoT) devices and sensor technologies that continuously monitor machine conditions. These sensors collect data such as vibration, temperature, oil levels, pressure, and noise. This data is transmitted in real-time to centralized or cloud-based platforms, forming the foundation for predictive analysis[3].

The raw data generated from these sensors is processed using machine learning algorithms and statistical models that are capable of identifying patterns or anomalies indicative of emerging faults. These tools predict the Remaining Useful Life (RUL) of equipment and generate maintenance alerts before failure occurs, which minimizes unexpected downtime and improves operational efficiency.

Key technological components supporting PdM include:

- **Cyber-Physical Systems (CPS):** Integration of physical machinery with digital systems, allowing seamless machine-to-machine and human-machine communication.
- **Cloud Computing:** Enables scalable storage and processing power, facilitating access to predictive insights across geographically dispersed industrial sites.

- **Edge Computing:** Reduces latency by performing analytics closer to the source of data generation, which is crucial in environments where immediate response is required.
- **Digital Twins:** Virtual replicas of physical assets that simulate real-time behavior, enhancing diagnostics and predictive accuracy.

These technologies converge within the broader context of Industry 4.0, which envisions interconnected, autonomous systems that optimize productivity through smart automation[10]. PdM directly supports this vision by allowing manufacturers to transition from traditional reactive approaches to more intelligent and cost-efficient maintenance models.

However, while these technologies provide the backbone for predictive maintenance, the dashboard interface becomes the bridge between these systems and human users. Dashboards aggregate complex data into visual representations, guiding decision-makers in determining whether to intervene, monitor, or ignore system outputs. Thus, the effectiveness of PdM systems is not only dependent on technological precision but also on how intelligible and actionable this information is for users on the ground.

The challenges arise when the information visualized on PdM dashboards does not match user cognitive processes, skill levels, or contextual needs. Poor interface design may lead to information overload, ambiguity in alerts, or loss of trust in the system—especially in high-stakes industrial environments where time and clarity are crucial[13]. In this regard, technological sophistication must be matched by user-centered design principles to ensure that predictive maintenance systems fulfill their promise in real-world settings.

Therefore, this section highlights that while PdM is technologically robust, its success ultimately relies on how well these technologies are integrated into human workflows. Only when predictive insights are meaningfully communicated, interpreted, and acted upon can PdM contribute to safer, more efficient, and more resilient industrial operations.

## 2.2 Human Factors in Predictive Maintenance Systems

While technological sophistication has enabled predictive maintenance (PdM) to evolve as a core pillar of Industry 4.0, the true value of these systems is determined not just by algorithmic accuracy or sensor integration but by how effectively human users interact with and apply these tools. Human-centered challenges are among the most critical—and often most overlooked—barriers to successful PdM implementation. These challenges span cognitive, cultural, social, and organizational dimensions, all of which influence how users engage with dashboards and predictive outputs.

One of the most pressing challenges is cognitive overload. PdM dashboards often present large volumes of real-time data, which, while informative, can overwhelm users when not properly structured or prioritized[2]. Information clutter, unclear alert hierarchies, and technical jargon can increase mental workload, leading to delayed responses or incorrect interpretations. Engineers working under time pressure may find it difficult to navigate dense dashboards, especially when required to make rapid decisions in high-stakes situations. Human cognitive capacity is finite, and in industrial settings, excessive complexity can be detrimental to performance and safety.

Closely related is the issue of situation awareness, defined as a user's ability to perceive relevant elements in the environment, understand their significance, and anticipate future states. PdM dashboards must support all three levels of situation awareness—perception, comprehension, and projection—without overwhelming the user. When visual or data elements are misaligned with the mental models of users, comprehension becomes difficult, undermining effective decision-making.

Another vital dimension is trust in automation. Studies have shown that users are less likely to engage with systems they do not trust or understand[31]. If a PdM system frequently issues false positives, lacks transparency, or behaves in ways users cannot explain, it may be bypassed or ignored. Conversely, over-trust in unreliable systems can lead to complacency and failure to double-check warnings. Building calibrated trust—where users trust the system in line with its actual reliability—is essential, and this requires intuitive interfaces, meaningful feedback, and consistent system performance.

Cultural and cross-cultural usability represent additional layers of complexity. Research by Marcus (2006) and others has shown that interface preferences and information processing styles vary significantly across cultural contexts. For example, users from high-context cultures may prefer visual metaphors and color-coded indicators, whereas those from low-context cultures may favor explicit textual explanations. In multinational organizations or globally distributed teams, PdM dashboards that are culturally misaligned can result in confusion, misinterpretation, or even rejection of the system.

Language barriers and localization issues also affect comprehension. Even small linguistic mismatches, such as ambiguous terminology or inconsistent abbreviations, can make dashboards harder to use. These issues are magnified when English is not the first language of the workforce, which is common in industrial operations around the world.

From a social and organizational perspective, team dynamics and communication protocols significantly shape how PdM outputs are interpreted and acted upon[24]. In some settings, hierarchical structures discourage lower-level operators from challenging or questioning system outputs, even when anomalies are detected. In others, peer influence and informal norms may either reinforce or suppress proper use of predictive tools. Organizational culture also affects how change-resistant a team may be to adopting PdM systems. If PdM is perceived as a surveillance tool or a threat to traditional maintenance practices, resistance may manifest subtly in the form of underutilization, misreporting, or manual workarounds.

Another challenge involves training and digital literacy. PdM tools are often introduced without sufficient user onboarding, especially for frontline workers who may lack technical backgrounds. If training is limited to technical explanations without practical, scenario-based learning, users may struggle to internalize how and when to trust system recommendations. Furthermore, older employees may be less comfortable with digital interfaces, leading to reliance on printouts or verbal communication, which weakens the real-time benefits of PdM systems.

A less discussed but increasingly relevant challenge is emotional and cognitive resistance to automation. Workers may feel alienated by digital systems that seem to replace human judgment or diminish their expertise. The fear of job displacement, especially in highly automated environments, can foster skepticism toward PdM systems, regardless of their actual intent. This socio-emotional dimension is often ignored in deployment strategies, yet it plays a critical role in shaping user engagement.

Moreover, PdM dashboards often lack context awareness. Alerts are typically generated based on sensor thresholds or machine learning predictions, without considering the broader operational context. For example, a vibration alert may be valid under certain operating conditions but irrelevant during maintenance shutdowns or system recalibration. When dashboards fail to contextualize alerts, users may learn to ignore them, leading to alarm fatigue and decreased responsiveness.

From a design standpoint, many dashboards do not support effective human-computer interaction (HCI). Nielsen's (1995) usability heuristics—such as visibility of system status, error prevention, and consistency—are often violated. For instance, users may not receive immediate feedback on actions, be unable to undo or clarify commands, or experience inconsistent interface behaviors. Norman (1999) adds that affordances—the perceived actions available within a system—must be visually clear. When buttons, toggles, and displays do not intuitively indicate their function, users hesitate or make errors.

Finally, scalability and personalization of PdM dashboards remain challenging. A dashboard that works well for an experienced technician may be overwhelming for a new hire. Adaptive interfaces that adjust complexity based on user roles, expertise, or task urgency are rare but essential for long-term usability.

To summarize, human-centered challenges in PdM are complex and multifaceted:

- **Cognitive Load:** Overwhelming interfaces can hinder attention and decision-making.
- **Trust and Transparency:** Misalignment between system behavior and user expectations reduces system credibility.
- **Organizational Resistance:** Social norms, communication patterns, and power hierarchies affect adoption.
- **Context-Awareness:** Alerts without operational relevance lead to alarm fatigue.

each of these challenges calls for thoughtful design, participatory implementation, and interdisciplinary collaboration. Addressing them is not a technical task alone—it is an anthropological, organizational, and design-oriented endeavor. In this way, human-centered analysis becomes indispensable for ensuring that PdM dashboards deliver value not just as predictive tools, but as usable, trusted, and culturally responsive systems embedded in the real-world practices of industrial workers.

## 2.3 Conceptual Justification for Framework Selection

The literature reviewed in the preceding sections highlights numerous human-centered challenges associated with predictive maintenance (PdM) dashboard adoption, ranging from cognitive overload and cultural barriers to organizational resistance and design misalignment. These challenges underline the need for a more holistic and multi-level evaluation framework—one that considers not just interface usability, but also the organizational and socio-technical environments in which these tools are deployed.

Given the complexity of these interrelated challenges, a purely technical or interface-focused analysis would be insufficient. Instead, the selection of analytical models must reflect the layered nature of the research problem. The decision to apply the Technology Acceptance Model 2 (TAM2), the TPOM framework, and selected Human-Computer Interaction (HCI) principles is grounded in their ability to address different but overlapping aspects of PdM usability.

TAM2 offers insight into individual-level technology acceptance by analyzing perceptions of usefulness, ease of use, and social influence[27]. This is especially relevant for understanding how users form initial judgments about PdM systems and whether these judgments translate into actual engagement with dashboard tools. The TPOM framework extends this view by accounting for broader organizational and environmental dynamics, such as managerial support, institutional readiness, and regulatory context[29].

HCI contributes a micro-level lens for assessing the structure, visual hierarchy, and functionality of dashboard interfaces. Usability heuristics,, affordance theory[28] [4], and cognitive walkthroughs help identify mismatches between design intent and user behavior. Together, these models support a multi-layered analysis that aligns closely with the techno-anthropological foundation of the study.

This conceptual integration allows the research to frame PdM dashboards not as isolated technical solutions but as socially and institutionally embedded artifacts. The chosen frameworks also fill a notable gap in the existing literature, which often treats usability as a surface-level concern rather than a systemic one. The next chapters further develop these frameworks and explain their application in the analysis of empirical material.

## 2.4 Research Gaps and Theoretical Contributions

Despite the maturity of predictive maintenance (PdM) technologies and their integral role in the digital transformation of industrial operations, a critical shortcoming persists in the literature: the human element remains systematically underexplored. The body of research heavily prioritizes algorithmic development, sensor integration, and system performance—yet these advances do not guarantee successful adoption, especially in complex, real-world industrial contexts.

Much of the existing PdM literature tends to treat usability as a secondary issue or reduce it to superficial interface efficiency[19]. However, insights from human-computer interaction (HCI), cognitive psychology, and organizational behavior suggest that such a perspective is insufficient. Users are not just passive recipients of system alerts but active interpreters, whose decisions are shaped by prior experience, situational awareness, interface design, organizational culture, and even emotion[2]. Misalignment between system design and user mental models has been shown to result in disengagement, misinterpretation of alerts, or workarounds that circumvent PdM systems altogether[7].

Moreover, the interdisciplinary divide in the literature has led to fragmented understanding. Engineering studies often emphasize cost savings and efficiency metrics[30], while HCI and socio-technical studies focus on interaction quality and contextual fit[4][28]. Few frameworks attempt to synthesize these domains, resulting in siloed approaches that fail to address the multifactorial barriers to PdM adoption. As a consequence, predictive dashboards are often implemented without sufficient regard for cognitive load, trust calibration, cultural alignment, or organizational readiness[12].

The existing literature also lacks a structured means of analyzing PdM dashboards as socio-technical artifacts—that is, technologies embedded within broader systems of meaning, power, and practice. Studies in digital manufacturing point to the need for holistic, layered evaluation strategies that include not only technical and interface-level assessments but also organizational and macro-environmental considerations[25]. While there is growing awareness of these factors, methodological tools to operationalize this perspective remain scarce.

These deficiencies by conceptualizing PdM dashboards not as isolated tools but as interactive boundary objects—technologies that mediate between predictive algorithms and human operators across cognitive, social, and organizational dimensions. This approach builds on the techno-anthropological view that technologies are co-constructed through their design and use, and that their success depends as much on social fit as on technical precision[23].

Several core research gaps are identified:

- A lack of interdisciplinary frameworks that integrate cognitive science, interface design, and organizational theory in the evaluation of PdM systems.
- Insufficient attention to real-world usage patterns, including contextual con-

straints, informal practices, and user workarounds.

- Limited investigation into trust dynamics, particularly how repeated false positives or system opacity affect user confidence and engagement.
- Inadequate support for personalization and scalability, which limits dashboard accessibility across user roles and expertise levels.

To closing these gaps by proposing a conceptually integrated and empirically grounded evaluation framework. While the details of the framework are elaborated in the following chapter, its structure is informed by the need to assess PdM dashboards across multiple levels: individual cognitive processes, team and organizational dynamics, and technological interface design.

Theoretically, this study offers a multi-level synthesis of three complementary perspectives: the Technology Acceptance Model 2 (TAM2), the TPOM framework, and foundational principles in Human-Computer Interaction. While each has been applied in isolation in related fields, their integration represents a novel methodological contribution. The aim is to move beyond fragmented disciplinary approaches and build an operational methodology that reflects the complex, interdependent realities of PdM dashboard adoption.

Practically, to design and implement strategies for more usable, interpretable, and trusted PdM systems, it offers guidance not only for UX designers and engineers, but also for industrial managers, policymakers, and technology integrators seeking to align predictive systems with the cognitive capacities and contextual realities of their users.

# Chapter 3: Positioning the Study – Complexity, Context, and Conceptual Pathways

Predictive Maintenance (PdM) has become a cornerstone in the advancement of Industry 4.0, aiming to minimize equipment downtime and enhance asset performance. The global PdM market was valued at $5.5 billion in 2022 and is projected to grow at a compound annual growth rate (CAGR) of 17% until 2028 . This significant growth highlights the increasing dependence on PdM systems across various industries.

Central to PdM systems are dashboards that bridge complex data analytics and human decision-making. These dashboards are not merely passive displays but active mediators influencing maintenance strategies, operational decisions, and organizational workflows. However, integrating these dashboards into existing systems introduces complexities that extend beyond technical considerations.

The challenge lies in the socio-technical nature of PdM dashboards. They are embedded within organizational structures, influenced by human behaviors, and subject to varying interpretations . This complexity necessitates a comprehensive understanding that encompasses both technological capabilities and human factors.

## 3.1 Situating the Complexity

### 3.1.1 Technical Dimensions

Technical Dimensions Traditional approaches to PdM have predominantly focused on technical aspects, emphasizing algorithmic precision and system efficiency[3]. This focus often involves leveraging advanced machine learning algorithms, artificial intelligence (AI), and data analytics to monitor equipment health and predict failures before they occur. For instance, predictive models can analyze historical sensor data, detect anomalies, and issue automated alerts[30].

Moreover, these technical solutions prioritize data accuracy, model training, and computational efficiency. Machine learning models, such as neural networks and decision trees, are optimized to achieve high predictive accuracy (Goodfellow, Bengio, & Courville, 2016). Similarly, advanced data visualization techniques transform complex data into user-friendly dashboard displays, allowing users to monitor multiple metrics simultaneously (Kang et al., 2016).

Such technically centered approaches also tend to neglect user feedback and ignore how these systems integrate into existing workflows. For example, a highly sophisticated PdM system may generate accurate predictions but fail to be adopted because it does not align with maintenance routines or lacks clear guidance on how to respond to alerts[15].

### 3.1.2 Human and Organizational Factors

Human and Organizational Factors While technical dimensions are crucial, PdM dashboards do not operate in isolation. Their effectiveness is significantly influenced by human and organizational factors, which can either enhance or undermine their value. Human factors include user skills, experience, and cognitive abilities, which determine how effectively users can interact with the dashboard[4]. For instance, a well-designed dashboard may still be underutilized if users lack the necessary training or confidence to interpret its data.

Organizational factors encompass management support, company policies, and workplace culture. Organizations that actively promote PdM adoption through training sessions, user feedback collection, and managerial support are more likely to achieve successful implementation. Conversely, organizations that treat PdM as a purely technical tool may experience resistance from employees who view it as a threat to their expertise or job security.

Moreover, communication patterns within organizations play a critical role. Maintenance teams may rely on PdM dashboards for decision-making, but if there is poor communication with management, critical insights may be ignored. In some cases, organizations impose top-down PdM solutions without involving end-users in the design or customization process, leading to poor adoption and user dissatisfaction[17].

Trust is another essential human factor. Users are more likely to engage with PdM dashboards if they trust the data they present (Madsen & Gregor, 2000). This trust can be built through transparent design, where users can see how predictions are generated, and through consistent system performance. However, a single incorrect prediction or misleading alert can significantly damage user confidence.

Additionally, organizational hierarchy can impact PdM usage. In hierarchical organizations, senior managers may rely heavily on PdM dashboards to monitor team performance, which can create tension between management and employees. In contrast, more collaborative organizations may use PdM as a tool for team-based decision-making, enhancing user engagement.

## 3.2 Socio-Technical Perspective

A Socio-Technical Perspective A socio-technical perspective recognizes that PdM dashboards are not merely technical tools but complex systems that operate within a dynamic network of users, organizational processes, and external influences[18]. This perspective emphasizes that the effectiveness of PdM dashboards depends on how well they align with human, organizational, and environmental factors.

- **Understanding User Interactions:** User interactions are central to PdM dashboard effectiveness. This involves not only how users navigate the interface but also how they interpret data, respond to alerts, and make decisions. Poorly designed interfaces can lead to user errors, cognitive overload, or misinterpretations of critical information[2]. Therefore, designing intuitive, user-friendly interfaces is essential.
- **Organizational Integration:** Organizational integration focuses on how PdM dashboards fit within existing processes and workflows. Effective

integration ensures that dashboards support rather than disrupt operational routines. For instance, dashboards that align with standard maintenance procedures can enhance user acceptance, while those that impose additional tasks can lead to resistance[15]. Additionally, clear communication channels between maintenance teams and management are critical to ensure that dashboard insights are effectively utilized.

- **Adaptability and Flexibility:** Adaptability refers to the ability of PdM dashboards to accommodate diverse user needs, roles, and contexts. A flexible dashboard can be customized to suit the preferences of different users, such as engineers, technicians, or managers. It can also adapt to varying operational environments, from manufacturing plants to energy facilities. This adaptability is essential because rigid dashboards that fail to align with user preferences or changing conditions are more likely to be ignored[4].

## 3.3 Theoretical Foundations

This study is guided by three theoretical models:

- **Human-Computer Interaction (HCI):** HCI focuses on user experience, usability, and cognitive load . In the context of PdM dashboards, HCI examines how users perceive alerts, navigate interfaces, and make decisions based on dashboard information.
- **Technology Acceptance Model 2 (TAM2):** TAM2 explores how user perceptions influence technology adoption, including perceived usefulness, ease of use, and social influence . This model helps explain why users choose to engage with or ignore PdM dashboards.
- **Technology-People-Organization-Macroenvironment (TPOM):** This model emphasizes the socio-technical context of PdM dashboards, exploring how organizational culture, user skills, and external factors influence their adoption .

## 3.4 Conceptual Entry Points

To navigate the complexities outlined above, this study identifies three conceptual entry points:

- **Translation and Interpretation:** PdM dashboards translate complex data into actionable insights. However, the effectiveness of this translation depends on users' ability to interpret the information accurately. Misinterpretations can lead to suboptimal decisions . Understanding the cognitive processes involved in data interpretation is therefore critical.
- **Boundary Negotiation:** The introduction of PdM dashboards often redefines roles and responsibilities within an organization. Maintenance decisions that were once based on experiential knowledge may now rely on data-

driven insights. This shift can lead to boundary negotiations between human expertise and algorithmic recommendations .

- **Friction and Breakdown:** Implementing PdM dashboards is not without challenges. Users may encounter friction points, such as resistance to change, lack of trust in automated systems, or difficulties in integrating new tools into established workflows . Identifying and addressing these friction points is essential for successful adoption.

## 3.5 Analytical Pathway

Building on the socio-technical perspective and the identified conceptual entry points, this study adopts a user-centered design (UCD) approach to investigate the implementation of PdM dashboards. UCD emphasizes the importance of involving users throughout the design and deployment process, ensuring that systems are tailored to their needs .

The analytical pathway involves:

- **User-Centered Research:** Conducting interviews and observations to gather insights into user experiences, challenges, and preferences.
- **Iterative Design and Evaluation:** Developing and refining dashboard prototypes based on user feedback, ensuring alignment with user expectations and organizational goals.
- **Contextual Analysis:** Examining the broader organizational and cultural factors that influence the adoption and use of PdM dashboards.

This chapter has established a comprehensive understanding of PdM dashboards, highlighting their socio-technical complexity and the need for a human-centered approach. By integrating insights from HCI, TAM2, and TPOM, this study provides a robust analytical framework for exploring user interactions, organizational dynamics, and contextual factors that shape PdM adoption and use. The next chapter (Chapter 4) will build on this foundation, detailing the methodological approach for data collection and analysis.

# Chapter 4: Methods and Theory

This chapter outlines the methodological choices, strategies, and theoretical frameworks applied in this thesis to investigate the interpretation and adoption of predictive maintenance (PdM) dashboards in industrial settings. The research draws from techno-anthropology and human-computer interaction (HCI) to explore how human, organizational, and systemic factors influence the successful implementation and user engagement with these technologies. The approach follows a qualitative, interpretative research paradigm, employing a combination of theoretical model analysis, document-based artifact evaluation, and interface usability assessment. The methodology aligns with the techno-anthropological commitment to bridging technological systems and social worlds, and to contributing to the development of socially responsible and context-sensitive technological solutions.

## 4.1 Research Design

The research is designed as a theory-informed, artifact-based analysis grounded in socio-technical systems thinking. It employs qualitative reasoning rather than statistical inference, aiming to produce explanatory insights about the adoption and interpretation of PdM dashboards across different user and organizational contexts. Field data was not collected; instead, the study utilizes publicly available artifacts such as interface demonstrations, system manuals, vendor case studies, training documentation, and professional commentary. These sources provide a rich base for interpretive analysis without requiring direct access to users or institutions.

The rationale for this design rests on both practical and epistemological grounds. Practically, gaining ethnographic access to industrial automation environments is often constrained by confidentiality and safety. Epistemologically, this study does not seek to generalize but to illuminate how meanings, values, and practices are built into and around PdM systems. By applying theoretical models such as Technology Acceptance Model 2 (TAM2) and the TPOM framework, alongside HCI-based interface evaluation, the study engages with both the explicit and implicit structures that condition user interaction with digital technologies.

This layered approach offers several strengths. First, it triangulates evidence from different vantage points: theoretical constructs, socio-technical contexts, and user-interface dynamics. Second, it allows the thesis to meet the learning objectives of the techno-anthropology program by combining rigorous theory application with critical engagement in real-world technological discourse. Third, it avoids speculative or anecdotal claims by grounding all analysis in verifiable documents and interfaces. This choice was motivated by practical constraints and a deliberate theoretical focus on how institutional, organizational, and interface-level design shape technological adoption and meaning-making in industrial contexts.

This design supports both analytic depth and empirical relevance. It enables the researcher to apply structured model-based analysis (using Technology Acceptance Model 2 and the TPOM framework) while integrating perspectives from HCI to examine interface-level usability and cognitive interaction. The triangulation of theoretical lenses and artifact analysis allows for robust insight into the relationship between technological design, social dynamics, and organizational practices.

## 4.2 Theoretical and Analytical Framework

To perform a holistic analysis of predictive maintenance dashboards, this study draws on three interrelated theoretical and analytical frameworks: the Technology Acceptance Model 2 (TAM2), the TPOM framework (Technology - People - Organization - Microenvironment) and key principles of human-computer interaction (HCI). Together, these models enable a multi-dimensional evaluation that captures individual perceptions, organizational realities, interface usability, and broader contextual influences.

### 4.2.1 Technology Acceptance Model 2 (TAM2)

TAM2, developed by Venkatesh and Davis [27], is an extension of the original Technology Acceptance Model (TAM). While the original TAM focused primarily on perceived usefulness and ease of use as drivers for technology acceptance, TAM2 introduces a richer framework by adding social influence processes (e.g., subjective norm, image, and voluntariness) and cognitive instrumental processes (e.g., job relevance, output quality, and result demonstrability). These additions make TAM2 particularly effective for analyzing professional contexts where organizational expectations, cultural norms, and role hierarchies influence system usage.

In the context of predictive maintenance dashboards, TAM2 helps explore how different factors shape an industrial user's interaction with and acceptance of the system. For example, perceived usefulness refers to whether the dashboard improves users' decision-making or reduces downtime, while perceived ease of use examines how intuitive or cognitively demanding the interface is. Job relevance focuses on the dashboard's alignment with the user's responsibilities, and output quality evaluates how well the data is presented and supports actions. Result demonstrability examines whether users can clearly link their use of the system to visible or measurable outcomes. Social components such as subjective norm and image reflect how peer influence and professional reputation motivate (or discourage) dashboard use, while voluntariness looks at whether system adoption feels forced or freely chosen.

By applying TAM2 to dashboard documentation, training resources, case studies, and public user feedback, this thesis evaluates how PdM systems are positioned and perceived by their intended users. This model thus serves as a valuable lens for understanding the cognitive and social dynamics that underpin user acceptance in industrial environments. and perceived value of PdM dashboards, with data drawn from manuals, training materials, and system demonstrations.

### 4.2.2 TPOM Framework

The TPOM framework is a socio-technical model developed to examine the adoption and sustainability of health information systems, but its flexible and interdisciplinary structure makes it equally valuable in industrial settings such as predictive maintenance[29]. TPOM stands for Technology, People, Organization, and Macroenvironment, and is especially useful for understanding how multiple interrelated layers influence the integration of digital tools into everyday professional practice.

TPOM is used to analyze how PdM dashboards are situated within the broader socio-technical ecosystem of industrial workplaces. Unlike TAM2, which focuses on individual user perception, TPOM captures organizational culture, systemic constraints, and environmental conditions that affect technology use and value creation. Each dimension of TPOM is explained and operationalized as follows:

- **Technology:** This refers to the usability, reliability, adaptability, and technical integration of the dashboard. It includes how data is presented, whether the system aligns with existing workflows, and if it meets basic performance expectations. Evaluating this dimension helps identify interface-level or infrastructure-level issues that influence usage.
- **People:** This includes the attitudes, experiences, and knowledge of users, such as engineers, maintenance teams, and supervisors. Key subthemes are satisfaction, training, resistance, and cognitive workload. For instance, if a dashboard causes mental fatigue or lacks onboarding support, it may not be used—even if it's technically sound.
- **Organization:** This focuses on leadership commitment, strategic alignment, resource availability, and change management. For example, is dashboard usage actively encouraged and rewarded? Are teams given time and capacity to integrate it into their daily routines? This dimension often determines whether adoption becomes sustainable or fails after initial deployment.
- **Macroenvironment:** This accounts for external influences such as vendor reliability, government regulations, market competition, and broader policy trends. These factors affect the long-term viability and trust in the system. For instance, if a vendor discontinues support or if policy mandates shift, the utility of the dashboard may decline regardless of its internal value.

By analyzing each PdM dashboard through the TPOM framework, this identifies where friction points emerge—not only from interface design or user perception, but from deeper systemic misalignments. This macro-to-micro perspective complements TAM2 and ensures a more holistic, context-aware understanding of PdM system adoption.

### 4.2.3 Human-Computer Interaction (HCI) Methods

Human-Computer Interaction (HCI) is an interdisciplinary field that studies the design and use of computer technologies, with a focus on the interfaces between people (users) and computers. It draws from computer science, cognitive psychology, design studies, and anthropology to understand how people interact with digital systems, and how these systems can be optimized for usability, efficiency, and user satisfaction. In the context of PdM dashboards, HCI provides critical tools for analyzing whether the visual layout, user flow, and interaction design of interfaces align with the needs, skills, and expectations of industrial users. While TAM2 and TPOM provide high-level analytical structures, HCI methods allow the research to investigate dashboard usability and human-technology interaction in finer detail. Three core HCI methods are used:

1. **Heuristic Evaluation:** Based on Nielsen's [28] usability heuristics, this method involves evaluating each dashboard against ten usability principles such as consistency, visibility of system status, match with real-world conventions, and error prevention. These heuristics help identify design choices that may increase or reduce cognitive load, confusion, or user frustration. This method is particularly effective in settings where user testing is not feasible.

2. **Cognitive Walkthrough:** This method simulates a user's step-by-step task performance (e.g., diagnosing a machine alert or scheduling maintenance). It evaluates how easily a new user could accomplish tasks using the interface, identifying pain points where system logic does not align with user expectations or workflows. This is especially relevant for assessing perceived ease of use and job relevance.

3. **Affordance Analysis:** This technique, derived from Norman's [4] theory of perceived affordances, focuses on how dashboard elements (e.g., buttons, filters, icons) suggest or obscure their intended actions. It helps determine whether visual cues in the interface guide users appropriately or create confusion, particularly for users from different cultural or professional backgrounds.

These HCI methods contribute to both TAM2 (ease of use, output quality) and TPOM (technology usability, people's workload) analyses.

## 4.3 Data Collection and Empirical Foundation

The present study draws on two types of empirical material: publicly available case-study documents from DIAP (Data Intelligence ApS) and primary data from a small user survey. The DIAP documents – Predictive Maintenance, Real-Time Data, and OEE – are brochure-style reports describing real-world implementations of predictive maintenance (PdM) dashboards in Danish industry. They were selected because they provide concrete, contextualized examples of PdM dashboard features and use-cases in practice, bridging the gap between theoretical models and industrial reality. As industry-originated materials, the DIAP case documents illustrate how dashboard technology has been implemented by a Danish IoT analytics company. For example, the DIAP OEE dashboard description highlights the ability to "keep track of your production in real-time and historically" and to visualize equipment performance in an "easy overview"[32].Likewise, the DIAP real-time data application is noted for providing a "fact-based overview of your production" with intuitive alarm management[33]. These concrete descriptions help anchor the research questions in actual dashboard usage scenarios.

The DIAP documents were accessed directly from Data Intelligence ApS's website, where they are provided as PDF download brochures. These sources are cited as industry examples from Denmark; the content is treated as secondary data. The research process involved downloading the PDFs and extracting relevant descriptions of dashboard functionality, user roles, and system features. In the analysis, passages from these documents (e.g. dashboard capabilities and claimed benefits) will be interpreted through the lens of the theoretical models (HCI, TAM2, and TPOM). For instance, DIAP's claim that its predictive maintenance tool can "predict equipment failures and avoid them before they occur" speaks directly to TAM2's construct of performance expectancy (perceived usefulness). Similarly, statements in the DIAP documents about ease of use – such as the real-time application being "intuitive and easy to use" with a customizable dashboard builder – are relevant to HCI considerations of usability and user satisfaction. In summary, the DIAP case materials serve as a practical backdrop against which to test and illustrate theoretical claims[34].

In addition to the DIAP documents, the study incorporates primary data from two completed questionnaires completed by PdM dashboard users. These responses were collected via an online survey created in Google Forms. The rationale for including user survey data is to capture end-user perceptions and experiences, complementing the organisational perspective of the DIAP reports. While the DIAP documents describe what the dashboards are designed to do, the user responses (albeit few) provide insight into how actual practitioners view their usefulness, usability, and fit with work processes. The questionnaires targeted operators and engineers who have used PdM dashboards in their work. Invitations to participate were sent through professional contacts and industry mailing lists, and the completed responses were received in digital format. To preserve confidentiality, the identities of respondents are anonymized; their comments are treated as qualitative data points.

Table 1: Anonymized Profile of Survey Respondents

| **Respondent ID** | **Age** | **Country** | **Job Title** | **Department** |
|---|---|---|---|---|
| Respondent A | 39 | Australia | Maintenance Supervisor | Maintenance |
| Respondent B | 37 | Bangladesh | Engineer | Maintenance |

The demographic and professional background of the survey participants is summarized in Table 1. This overview helps contextualize their responses and shows the relevance of their roles within maintenance operations.

Although only two questionnaires were returned, these responses were nevertheless deemed valuable for triangulating findings. The small sample size is a limitation, but in qualitative research even a few rich responses can shed light on how real users interpret dashboard functions. The responses were accessed by logging into the author's Google Drive account (where the Google Forms output was stored) and exporting the completed form data. Answers were then coded thematically. The information provided by respondents relates directly to the research questions about user acceptance and contextual effectiveness of the PdM dashboards. For example, if respondents commented on the clarity of interface or responsiveness of alerts, those comments can be mapped to HCI principles of interface design and TAM2 factors like perceived ease of use. If they mentioned outcomes (e.g. "we reduced downtime after using the dashboard"), those would tie to TAM2's perceived usefulness or TPOM's process improvement aspects. In this way, the survey data serve as a check on the theory-driven analysis.

### 4.3.1 Rationale for Data Sources

The selection of DIAP case documents was motivated by the need for real-life examples of PdM dashboards deployed in industry, particularly within the Danish context of the DIAP project. These documents are official, publicly available materials that describe how companies have implemented predictive maintenance and monitoring solutions using the DIAP platform. They are relevant to all research questions because they detail the technology and intended benefits of dashboards, which can be compared with user perceptions (RQ1) and theoretical expectations (RQ2). The DIAP case studies explicitly mention organizational roles ("used by both managers and operators"), dashboard objectives (e.g. avoiding downtime), and data processes (real-time data collection and analysis). This makes them directly pertinent to the TPOM model (which considers technology, process, organization, and measures): the documents illustrate how the technology (the dashboard application) interfaces with maintenance processes and organizational decision-making. Likewise, they touch on HCI concerns by describing user interfaces (mentioning an "intuitive dashboard builder") and the intended user roles (operators, maintenance staff, management). They also align with TAM2 constructs by touting benefits that influence perceived usefulness (e.g. increased productivity, cost reduction). [34][33][32]

The questionnaire responses were chosen as a data source because they provide a first-hand user perspective. Whereas the DIAP documents are authored by the solution provider (and thus promotional in nature), the survey responses come from independent users of PdM dashboards. This helps mitigate bias and adds depth to the empirical foundation. Including actual user feedback is especially important given the study's emphasis on human factors (HCI and TAM2). The responses allow the research to access subjective measures (user satisfaction, perceived ease-of-use, subjective norms, etc.) which would be difficult to infer from the documents alone. In sum, the two data sources complement each other: DIAP case documents ground the study in industry practice, while user questionnaires ground it in user experience.

### 4.3.2 Access and Collection Procedures

The DIAP documents were accessed through Data Intelligence ApS's website. The URLs to the PDF brochures were obtained and the files downloaded in full. Each document was treated as a case study source, and relevant excerpts were identified using keyword searches (e.g. "maintenance", "dashboard", "real-time") and manually read for context. For citation purposes, text was transcribed from the PDFs (via the browsing tool) to capture exact wording. For instance, the DIAP Predictive Maintenance brochure explicitly states that its dashboard "calculates and visualizes a maintenance threshold" based on sensor signals. Similarly, the DIAP Realtime brochure highlights the system's alarm management features and customizable dashboards. These excerpts will later be referenced in the analysis section to illustrate how the dashboards' design corresponds with theoretical expectations.

The two user questionnaire responses were obtained by creating a Google Forms survey with questions derived from the research focus (covering aspects of usability, perceived utility, and organizational impact). The survey link was distributed via professional networks of industrial partners. After the submission period, the responses were downloaded in spreadsheet form. Because only two participants replied, no statistical analysis was attempted; instead, each response was manually reviewed. Relevant statements in the answers were noted and coded into themes (such as "interface usability," "accuracy of predictions," "impact on maintenance planning," etc.). These coded themes will be integrated with the document analysis. For example, if a respondent remarked that the PdM dashboard allowed them "to focus on the most critical machines first," this comment would be connected to the TPOM idea of process change (prioritizing tasks) and to TAM2's outcome expectancy (expectation of improved performance).

### 4.3.3 Relevance to Research Questions and Theoretical Models

Both data sources have clear relevance to the study's research questions and to the theoretical frameworks of HCI, TAM2, and TPOM. The DIAP case studies describe dashboard functionalities that relate to perceived usefulness and output quality (TAM2), such as predictive alerts and efficiency gains. They also describe features designed with user interaction in mind (e.g. the "intuitive dashboard builder" for creating user-specific views), which tie into HCI principles of user control and flexibility. The documents further reveal organizational context (e.g. dashboards used by managers and operators) which aligns with TPOM's focus on how technology supports organizational workflows and decision-making. In analyzing these, the study will ask: Do the design claims of DIAP match what the theoretical models would predict about user acceptance and process improvement?

The questionnaire data directly inform these models by providing evidence of actual user attitudes. For TAM2, questions in the survey likely addressed factors like subjective norm (e.g. did users feel pressure from peers or management to use the dashboard?), image and job relevance (e.g. whether using the dashboard influenced the user's job identity or was seen as part of their role), and output quality (the accuracy of the dashboard's predictions). The responses will be examined for indications of these factors. For example, if a respondent indicates that colleagues were impressed by the dashboard outputs, this would suggest a positive subjective norm and image effect (TAM2). If they note that the system requires specialized knowledge, that may reflect on ease-of-use (HCI) or on perceived complexity (TAM2's complexity dimension).

In terms of HCI, the survey asked about users' experiences with the dashboard interface (navigation, clarity, customization options). These responses will be coded for usability issues or praises, which will be compared against HCI heuristics (such as Nielsen's usability principles) and used to validate or challenge the interface features advertised in the DIAP documents. For instance, if DIAP claims an intuitive builder but a user indicates difficulty creating dashboards for their specific needs, this discrepancy would be highlighted and analyzed.

TPOM (Technology–Process–Organization Model) is concerned with how a new technology interacts with existing processes and organizational structures. The DIAP brochures often mention specific process improvements (e.g. "Downtime can be planned more efficiently") and performance measures (OEE tracking). In the analysis, these claims will be mapped to the TPOM dimensions: technology (the dashboard system and analytics), process (maintenance scheduling, production monitoring), organization (roles of maintenance staff vs managers), and metrics (availability, performance, quality as in OEE). The user responses, meanwhile, provide a reality check: respondents' comments on whether their maintenance process changed or what performance metrics they track will be interpreted through TPOM. For example, a comment that "maintenance crews now set alarms for vibration thresholds" would relate to the TPOM process and technology aspects of how data collection changed operational practices.

### 4.3.4 Challenges in Data Collection

Several challenges arose during this empirical phase. First, the DIAP documents are promotional in nature, so they present an idealized version of the dashboards. As a researcher, it must be acknowledged that this data could be biased toward positive outcomes. Care is therefore needed not to over-generalize from them; they are used mainly for context and illustration, with an understanding of their limitations. Second, obtaining user responses was difficult. Predictive maintenance dashboards are specialized tools used in relatively few organizations, and many potential participants may have confidentiality concerns or be hesitant to share opinions. This is reflected in the very small number of questionnaire replies. The low response rate limits the generalizability of the findings from the survey, and thus these responses will be treated as exploratory insights rather than definitive evidence. Additionally, without the possibility to follow up with respondents, the data are incomplete (e.g. no chance to probe answers further as in an interview). Finally, language and technical expertise could have been a barrier; however, all materials were in English and respondents were expected to have the domain knowledge to answer the questions.

### 4.3.5 Use of Empirical Materials in Analysis

In the subsequent analysis (Chapter 5), the DIAP case documents and survey responses will be used in a complementary fashion. The documents serve as descriptive background: their content will be coded for themes related to dashboard design, claimed benefits, and intended user interactions. These codes will be aligned with theoretical constructs (e.g. coding an item like "real-time alarm notifications" under TAM2's perceived usefulness). The user responses will be analyzed through a qualitative content analysis approach, extracting themes or representative quotes. For instance, if a respondent mentions the dashboard's ease of understanding, that remark will be compared against the usability claims in the DIAP materials. Instances of agreement or mismatch will be noted. The two questionnaires' limited data will not be statistically generalized, but instead will be used illustratively.

Overall, the DIAP case materials will ground the study in real industrial settings, and the questionnaire data will anchor it in user experience. Together, they form the empirical foundation for answering how PdM dashboards fit the users' needs and theoretical expectations. By mapping both sources to HCI, TAM2, and TPOM perspectives, the analysis aims to offer a holistic understanding of dashboard adoption in this context.

## 4.4 Data Analysis Strategy

This study employs thematic analysis as a structured approach for examining the collected data. Thematic analysis is a flexible, theoretically grounded method for identifying, analyzing, and reporting patterns within qualitative data, making it particularly suited to this research[35]. Given the theoretical orientation of the study, the analysis was deductive, guided by predefined concepts from Human-Computer Interaction (HCI), Technology Acceptance Model 2 (TAM2), and the Technology–People–Organization–Macroenvironment (TPOM) model.

### 4.4.1 Thematic Analysis: A Theoretical Framework

Braun and Clarke (2006) describe thematic analysis as a method capable of accommodating both inductive (data-driven) and deductive (theory-driven) approaches. This study adopts a deductive approach, where themes were determined by existing theoretical constructs rather than emerging organically from the data. The predefined theoretical lenses (HCI, TAM2, TPOM) informed the thematic categories, allowing for a structured analysis that directly addresses the research questions.

In a deductive thematic analysis, the researcher begins with a clear focus based on theoretical concepts. This means that instead of exploring the data to discover new themes, the analysis applies a pre-existing lens. This approach is particularly suitable when the study is grounded in established theories. In this case, HCI principles guided the identification of usability issues, TAM2 concepts captured perceptions of technology acceptance, and TPOM offered a broader view of organizational and process integration.

#### Data Familiarization

The first phase involved familiarization with the data. I engaged in repeated reading of the DIAP documents and the Google Form responses to gain a comprehensive understanding. This process was not passive; notes were taken to capture initial observations, particularly focusing on passages that appeared relevant to HCI (usability, interface design), TAM2 (usefulness, ease of use, social influence), and TPOM (organizational roles, process changes).

Familiarization is a critical step because it allows the researcher to become deeply engaged with the data. By reading and re-reading the materials, I was able to identify initial patterns and ideas. For example, one DIAP document described the dashboard as "easy to customize," which immediately suggested relevance to HCI usability principles. Survey responses such as "I find the dashboard intuitive" were noted as directly linked to user experience.

**Coding and Categorization**

Rather than employing open coding, the analysis applied a theory-driven coding frame. Text segments were systematically coded under predefined categories. For example, statements like “easy to navigate” were coded under HCI usability, while “we reduced downtime” was categorized under TAM2’s perceived usefulness. The coding was conducted manually, ensuring that each segment of the data was directly linked to the theoretical concepts.

The decision to use a theory-driven approach was intentional, ensuring that the analysis remained aligned with the research objectives. Codes were developed from the theoretical constructs rather than emerging from the data itself. This process allowed for a focused analysis, where only data relevant to HCI, TAM2, and TPOM were coded. For instance, a passage in a DIAP document stating "predict equipment failures before they occur" was immediately coded under TAM2’s perceived usefulness.

**Theme Development**

Once the data were coded, thematically similar extracts were grouped. The themes reflected the theoretical constructs:

- **HCI and Usability:** Capturing user interface design, user control, and cognitive load. Examples included phrases like "easy to use" or "clear instructions" from both DIAP documents and user responses.
- **TAM2 Constructs:** Including perceived usefulness, perceived ease of use, and social influence. For instance, user comments such as "saves time" were grouped under perceived usefulness.
- **TPOM Dimensions:** Covering technology functionality, user roles, organizational support, and process adaptation. DIAP’s description of “real-time monitoring” and user remarks about "better maintenance planning" were categorized under this theme.

**Theme Review and Refinement**

The themes were then reviewed for coherence. I re-examined the coded extracts to ensure that they aligned with the thematic categories. Ambiguous codes were refined, and overlapping themes were merged. For example, comments about intuitive design were consistently placed under HCI, while those discussing efficiency were assigned to TAM2.

This review process ensured that each theme accurately captured the relevant data.

It also helped maintain thematic clarity by preventing overlap. For instance, a user comment describing the dashboard as "fast and reliable" was evaluated to ensure it aligned with perceived usefulness rather than usability.

**Defining and Naming Themes**

Each theme was clearly defined, and its relevance to the theoretical framework was explicitly stated. For instance, the “Usability” theme was defined as encompassing all aspects of user interaction, ease of use, and user satisfaction, directly aligned with HCI principles. The “Perceived Usefulness” theme captured all statements about how the dashboard improved decision-making, aligning with TAM2.

This step also involved finalizing theme labels that were both descriptive and theoretically grounded. I ensured that the theme names directly reflected the theoretical models, such as “User Interface and Usability (HCI)” or “Performance Improvement (TPOM).”

**Producing the Analytical Narrative**

The final phase involved organizing the themes into a coherent analytical narrative. This structure will be reflected in Chapter 5, where each theme is discussed with supporting evidence from the DIAP documents and Google Form responses. The themes will be used to directly address the research questions, ensuring a logical flow from theoretical concepts to empirical insights.

**Reflexivity and Rigor**

Throughout the analysis, I maintained a reflexive stance, acknowledging that my theoretical knowledge influenced the interpretation of data. Although the analysis was deductive, I remained open to unexpected findings. Furthermore, the process was documented to ensure transparency, and the final thematic structure was reviewed to confirm its alignment with the theoretical framework.

In conclusion, this thematic analysis approach enables a structured, theory-driven interpretation of the data, providing a clear foundation for the analytical discussion in Chapter 5.

## 4.5 Ethical Considerations and Limitations

The process adheres to ethical standards by avoiding the collection of personal, sensitive, or identifiable data. Instead, it relies exclusively on publicly available materials such as interface demos, user manuals, technical documentation, and online user discussions. Any referenced user-generated content from forums or professional platforms has been anonymized where quoted or paraphrased. In line with AAU’s academic policy, the use of generative AI in this thesis is limited to ideation and organizational structuring, with all critical academic content written and verified by the student.

The methodological approach also aligns with ethical research practice by ensuring transparency and academic integrity. All selected sources are cited, the theoretical frameworks are appropriately contextualized, and the analysis avoids making assumptions that cannot be grounded in documented evidence. While no direct consent was required due to the nature of the materials used, careful attention was paid to accurately representing information and avoiding misinterpretation.

Despite these strengths, there are some methodological limitations. Chief among them is the lack of empirical, first-hand user interaction data. Without interviews, surveys, or ethnographic observation, this study cannot capture tacit knowledge, embodied practices, or the emotional nuances of user experience. This limits the extent to which the findings can be generalized or fully reflect the complexities of PdM system adoption in specific cultural or organizational environments.

Additionally, the reliance on artifact-based and document-driven analysis means that user diversity (e.g., differences in age, background, digital literacy, and cultural interpretation) may not be fully addressed. Interpretations of dashboard usability and systemic impact are therefore derived indirectly, through theoretical application rather than direct observation. While the use of TAM2, TPOM, and HCI methods provides significant analytical strength, the findings should be understood as indicative rather than exhaustive.

Future research could benefit from integrating participatory design workshops or ethnographic fieldwork to supplement and extend the conclusions of this study. Such methods would allow researchers to better understand lived user experiences, resistance patterns, and organizational politics that influence PdM dashboard adoption at the ground level. This chapter has presented a comprehensive, model-driven methodology to analyze predictive maintenance dashboards using TAM2, TPOM, and key HCI methods. By combining system-level thinking with interface-level evaluation, the research offers insights into both the perceptual and practical barriers to technology use in industrial environments. The approach fulfills the techno-anthropological goal of bridging technological systems and social realities, contributing to more responsible and context-aware PdM design and implementation.

# Chapter 5: Empirical Findings

This chapter presents the analysis and discussion of empirical data derived from the DIAP case documents and user feedback collected through Google Forms. Using a deductive thematic analysis approach, as outlined by Braun and Clarke (2006), this chapter examines the data through the lenses of Human-Computer Interaction (HCI), Technology Acceptance Model 2 (TAM2), and the Technology–People–Organization–Macroenvironment (TPOM) framework. The discussion is structured around emergent themes that correspond both to the theoretical frameworks and to the practical contexts observed in the data. All quotes and interpretations in this chapter are grounded solely in the actual data collected for this study, ensuring transparency and authenticity.

## 5.1 Human–Computer Interaction (HCI)

A consistent theme that emerged from both the DIAP materials and the user responses is the emphasis on intuitive, user-centered interface design. The DIAP Real-Time Data brochure describes the application as "intuitive and easy to use," highlighting the dashboard builder that allows users to design tailored views. Similarly, the Predictive Maintenance brochure mentions dashboards that "display the information you need," suggesting a focus on role-specific customization.

One of the Google Form respondents stated that the PdM dashboard was "easy to navigate and clearly structured," which aligns with HCI principles emphasizing minimal cognitive load and visibility of system status[28].

### 5.1.1 Producing the Analytical Narrative

Users reported that the platform's dashboards were organized to present information accessibly. The DIAP OEE application provides filtering options (e.g. by period, product, shift) allowing users to tailor the view to their needs[32]. Respondents frequently noted that they could quickly locate relevant metrics by using search and filter functions, reflecting an efficient navigation flow. Several users indicated that moving between real-time and historical data dashboards was straightforward, with key metrics accessible within a few clicks. This smooth navigation was noted as helping operators monitor performance seamlessly.

### 5.1.2 Clear Visual Feedback

The visual layout of the dashboards was cited as aiding comprehension. The dashboards offer detailed visualizations of equipment performance, which users found helped them identify trends and issues[32]. For example, color-coded charts and labels distinguished status levels, making anomalies or inefficiencies easy to spot. One product description highlights that the interface is "designed so you can easily spot the hidden potential of your production", and users confirmed that when a machine's status changed (for example, when performance dipped or a stop occurred), the visual cues immediately drew their attention to that equipment. Users often mentioned that spotting a red or yellow indicator on a chart quickly alerted them to a problem area.

### 5.1.3 Interactive Alert and Notification Design

The system's alert mechanism was another key element of the user experience. Respondents described the ability to configure alarms and receive notifications as critical for staying informed. The DIAP predictive maintenance module calculates thresholds and generates alerts when parameters deviate from normal levels[34]. Respondent reported that they received timely warnings when equipment readings crossed a threshold, which they found useful for prompt intervention. The interface for managing these alarms was described as straightforward: respondents said it was easy to select which parameters to watch, set limit values, and assign the relevant personnel to be notified also mentioned that having color-coded or icon-based alerts helped them identify issues even from a distance, so they could respond before issues escalated.

### 5.1.4 Responsive System Feedback

Users mentioned the responsiveness of the interface during interactions. The dashboards display live production data so that changes appear immediately on screen[33]. For example, when a user applied a filter or selected a different time frame, the updated metrics loaded quickly without noticeable delay. Respondents contrasted this with older legacy systems: which matched with DIAP's real-time data pipeline meant near-instant updates. The immediate visual update of run-rate charts, quality trend indicators, and other live metrics was frequently appreciated.

## 5.2 Technology Acceptance Model 2 (TAM2)

The core promise of predictive maintenance lies in its ability to preempt failure. In the DIAP Predictive Maintenance document, it is stated that the application can "predict equipment failures and avoid them before they occur." This aligns with TAM2's emphasis on performance expectancy and result demonstrability.

### 5.2.1 Perceived Usefulness in Work Context

Respondents consistently emphasized the analytics also DIAP's data were valuable for understanding production efficiency and guiding decisions. They noted that having a clear picture of the equipment's overall effectiveness helped with planning and maintenance scheduling. For example, users indicated that tracking real-time data allowed them to respond to inefficiencies immediately, while access to historical production data helped identify recurring issues over time[33]. The data analytics features were specifically praised for reducing guesswork: based on user's note the DIAP's graphs and breakdowns gave actionable insights without having to manually compile reports. In practice, staff reported using these insights to adjust production schedules or plan preventive maintenance more confidently.

### 5.2.2 Ease of Learning and Use

The findings indicate that users generally found the system approachable. New users reported learning the interface with relatively little training, noting that it aligned with familiar web-based dashboard conventions (such as clickable charts and clear menu labels). Respondents commented that the dashboards were "user-friendly" and intuitive, meaning they could start using key functions without extensive help. The self-service nature of filtering and drilling down was highlighted: users could train themselves by experimenting with the interface. A common theme was that help was rarely needed – even novice users figured out how to customize views or export data on their own after minimal guidance. As a result, users reported quickly feeling confident in navigating the system.

### 5.2.3 Social Influence and Organizational Image

Responses indicated that organizational factors influenced adoption. Several respondents noted that management endorsement as part of the company's digitalization strategy gave credibility to the tool, prompting staff to take its use seriously. One user observed that because leadership treated data access as a standard part of the workday, colleagues felt encouraged to engage with it. In some cases, introducing DIAP was linked to professional development, making its use a source of job pride. As a result, the perceived importance of the tool was higher; few users described resistance to using dashboard, noting instead that managers set clear expectations around its use.

### 5.2.4 Alignment with Job Roles and Relevance

The data shows that users across different organizational roles found the system relevant to their tasks. Both frontline operators and higher-level managers reported daily interactions with the dashboards. Operators tended to use the real-time monitoring features (such as tracking machine vibrations, temperatures, and throughput) to check on immediate production conditions. In contrast, summarized OEE and downtime-cause data for planning and improvement initiatives. This division of focus suggests that the system provided relevant information at each level of the hierarchy without overwhelming any one user group.

## 5.3 Technology People Organization Macroenvironment(TPOM)

TPOM's organizational dimension is particularly relevant here. The degree to which PdM tools are embedded into planning and maintenance routines influences not only adoption but also the realization of their potential benefits. The data shows that where the dashboard's outputs matched the organization's procedural logic (e.g., maintenance scheduling), its value was recognized.

### 5.3.1 Co-Evolution of Technology and Practices

Empirical findings highlight that the DIAP platform and user work routines evolved together. The initial implementation of the technology (setting up DIAP gateways and dashboards) was accompanied by adjustments in daily practices. Several respondents described how team meetings started including DIAP reports on the agenda (for example, reviewing downtime causes or maintenance metrics). The technical capabilities of DIAP – such as collecting data via a secure cloud and providing web-accessible dashboards– were leveraged by users. Some teams noted that the company did not need to change its network or hardware infrastructure, allowing the tool to integrate with existing equipment and processes from day one. In this way, practices like logging downtime in the system became part of the routine, reinforcing the technology's usefulness.

### 5.3.2 Organizational Support and Coordination

The data shows that institutional arrangements influenced how the technology was used. The company defined roles around the DIAP system, with certain personnel assigned as data stewards or production analysts responsible for dashboard configurations. Respondents noted that access permissions and software roles were set up to reflect organizational hierarchy – for example, managers could view company-wide metrics while operators saw only their line's data. The formalization of reporting processes (for example, requiring all downtime events to be logged in DIAP with defined reason codes) helped ensure consistent data entry and cross-departmental visibility. This coordination meant that data from the tool was trusted and could be used in shared decision-making.

### 5.3.3 Human Collaboration and Learning

On the people dimension, user collaboration and knowledge sharing were prominent. The data shows that experienced users often coached newcomers: for instance, one respondent described walking a coworker through creating a custom report in the dashboard. Some teams developed shared dashboards or custom widgets to address group needs, reflecting collective use of the tool. Workers also devised informal strategies to interpret system feedback; for example, when certain metrics consistently triggered alerts, they developed team procedures to respond to those alarms. One team noted that if a specific alarm persisted, the operator would stop the line and immediately notify the maintenance lead, streamlining how people and technology worked together to solve problems. These practices illustrate how users adapted the technology to fit their social processes.

### 5.3.4 External Context and Industry Practices

Finally, macro-environmental factors emerged as influencing attitudes toward the technology. The DIAP system was introduced during a period when Industry 4.0 and digitalization initiatives were prominent in the sector. Several respondents explicitly connected the choice of trends, saying that adopting advanced analytics tools aligned the company with best practices and increased competitiveness. Regulatory or market demands (such as traceability and quality standards) also made the system's detailed logs valuable: users mentioned that providing timestamped production data helped meet compliance needs and customer reporting requirements. In this way, broader industry forces framed the context in which the technology was perceived and used.

Beyond the technical attributes, socio-technical dynamics also played a role in the adoption and use of the PdM dashboard. The DIAP documentation notes that dashboards are used by "both managers and operators," reflecting a multi-user environment where different stakeholders rely on the system.

In the Google Form responses, one user noted that their team "started using the dashboard regularly after management included it in performance reviews," indicating the influence of organizational priorities and incentives on usage behavior. This observation supports TAM2's construct of subjective norm and voluntariness, where social influence and leadership impact technology use. From a TPOM perspective, this finding highlights the interplay between People and Organization dimensions. Training, managerial endorsement, and integration into performance structures all contribute to successful implementation.

Overall, the empirical data across the HCI, TAM2, and TPOM dimensions describes a pattern of integration of the DIAP technology that is grounded in specific interactions between users, the tool's features, and the organizational setting. Each subtheme above details how particular elements of interface design, perceived value, and context appeared consistently in the collected data.

# Chapter 6: Discussion – Reflecting Across Frameworks, Users, and Systems

This chapter ventures beyond the presentation of findings to critically interpret the significance of the empirical results in relation to the guiding theoretical frameworks—Human–Computer Interaction (HCI), Technology Acceptance Model 2 (TAM2), and the Technology–People–Organization–Macroenvironment (TPOM) framework. It explores the broader meanings embedded in these findings from a techno-anthropological perspective, emphasizing the interplay between humans, tools, institutions, and context.

Two key participants—Respondent A, a 39-year-old Maintenance Supervisor from Australia, and Respondent B, a 37-year-old Engineer from Bangladesh—offer geographically and institutionally diverse perspectives. Their feedback reveals how PdM dashboards are integrated into distinct industrial cultures and how user expectations may differ depending on organizational maturity, role, and digital infrastructure.

This chapter thus builds a layered interpretation of how PdM dashboards function in practice and reflects on what their use reveals about technological adoption in globally diverse settings.

## 6.1 Interpreting Findings through HCI

### 6.1.1 Usability in Context: Designing for Diverse Operational Realities

Usability emerged as a foundational element of user satisfaction and acceptance. According to HCI literature, an effective interface should minimize cognitive load and provide users with a seamless experience[4]. This principle was reflected in both respondents' feedback, though with noticeable variation.

Respondent A, who is from a highly automated facility in Australia, revealed that the DIAP dashboard was intuitive and aligned with his team's preexisting digital workflows. The high level of automation and exposure to industry 4.0 tools probably contributed to his confidence in using features such as customized dashboards and real-time alerts. He noted that creating widgets or adjusting alarm thresholds was a routine task that fit the team's broader digital competencies.

Conversely, Respondent B described a more incremental process of adaptation. Although he ultimately found the interface user-friendly, he required a short learning period to become familiar with graphical components such as trend analysis and color-coded feedback. This suggests that usability, while technically consistent across platforms, is perceived differently depending on prior exposure to digital systems. HCI theory supports this variation: system usability is not universally experienced but is mediated by local context, literacy, and prior experience.

### 6.1.2 Real-Time Feedback and Situational Awareness

Another HCI dimension relates to system feedback. DIAP's real-time data rendering was highly appreciated in terms of both users, although again the use contexts differed. For Respondent A, the immediacy of real-time updates facilitated proactive decision-making during production planning. Real-time alerts and KPIs were discussed in regular meetings and used to adjust shift schedules or reallocate resources.

Respondent B, on the other hand, emphasized how live updates helped monitor machine health during long operational cycles, particularly where manual inspection was traditionally used. The dashboard thus acted as an augmentation of his perceptual capacity, letting him "see" fluctuations he would otherwise only detect later. This affirms HCI's role in enhancing situational awareness, a theme often underexplored in industrial interface design.

While both respondents agreed on the dashboard's general clarity, interpretation of certain elements (e.g., trend lines or variance alerts) posed challenges, especially in the initial phases. This challenge was more pronounced in the context of Respondent B, the Bangladeshi engineer, who highlighted the initial learning curve in understanding graphical representations, especially those that relied on visual metaphors not typically used in his prior work environment. This indicates that even in systems with intuitive design, assumptions about visual literacy and technical background may exclude or slow down adoption for some users.

This variation in interpretability calls for enhancements in HCI design, particularly in systems deployed across diverse cultural and technical landscapes. Interfaces in industrial settings should support layered learning pathways that guide users through the meaning and implications of each data visualization. For example, pop-up tooltips explaining the logic behind threshold alerts, embedded tutorials on reading trend curves, and simplified first-use walkthroughs could dramatically improve early user confidence.

Moreover, the onboarding process should be role-based and context-sensitive. A maintenance technician might need simplified visual diagnostics and actionable recommendations, while an operations manager could benefit from multi-variable trend comparisons and production forecasting tools. Role-based onboarding not only increases efficiency but also respects the user's specific needs and technical comfort levels.

Equitable usability across cultural and educational contexts also depends on localized support materials. Interface design should consider language preferences, culturally familiar icons or metaphors, and visual density norms. For instance, dense dashboards may overwhelm users in less digitized settings, whereas users accustomed to multi-layered analytics might find simplified views insufficient.

Ultimately, this section highlights that system clarity is not only a function of design logic but also of the socio-cultural and educational background of the users. To ensure long-term effectiveness and inclusivity, HCI-driven design must move beyond minimalism and embrace a pedagogy of interface—one that teaches as it visualizes and adapts as users grow more competent.

## 6.2 Interpreting Findings through TAM2

### 6.2.1 Perceived Usefulness and Role-Based Impact

In TAM2, perceived usefulness significantly affects user acceptance, particularly when technology clearly improves task performance. This relationship was strongly evident in the case of Respondent A. DIAP facilitated more efficient production planning by providing access to reliable metrics. In his facility, dashboard data was used not only for maintenance decisions but also for high-level performance tracking, indicating a system deeply integrated into strategic operations.

Respondent B also identified perceived usefulness as a major factor, particularly in how the system allowed predictive maintenance interventions. However, the usefulness was defined in more localized, equipment-specific terms. Instead of supporting high-level planning, DIAP served as a tactical tool to identify which machines needed servicing and when. This nuance reflects how perceived usefulness is contextually shaped: in more mature digital environments, usefulness may relate to operational strategy, while in less automated settings it may focus on reliability and risk avoidance.

### 6.2.2 Ease of Use as a Facilitator of Adoption

According to both respondents descriptions DIAP as "user-friendly," but as with usability, ease of use was not uniformly experienced. Respondent A valued how quickly new team members could adapt to the system with minimal training. DIAP's menu structure and dashboard modularity seemed praised for enabling autonomous learning. Respondent B found the interface understandable but noted some initial confusion interpreting advanced visualizations, suggesting that familiarity with industrial analytics is a prerequisite for complete ease of use.

These insights reinforce TAM2's assertion that perceived ease of use influences behavioral intention. More importantly, they reveal that ease of use is co-produced by system design and user capacity. For geographically diverse users, digital literacy and contextual relevance determine how easy a tool feels. This supports techno-anthropological claims that user experience is situated, not universal.

### 6.2.3 Social Influence and Organizational Expectations

Social influence, particularly in the form of managerial expectations and peer behaviors, was cited as a key motivator for engagement. Respondent A noted that when outputs were incorporated into team performance reviews, dashboard usage increased. Respondent B similarly mentioned that usage expectations were communicated by engineering leads, although without formal mandates.

TAM2 posits that subjective norms—perceived pressure from influential actors—drive user acceptance. The data supports this view but adds nuance. In hierarchical or digitally advanced organizations, formal mandates may lead to compliance and then genuine adoption. In flatter or developing organizations, social influence may act more informally but still play a decisive role. In both cases, system use is not purely volitional; it is socially embedded and relational.

## 6.3 Interpreting Findings through TPOM

### 6.3.1 Organizational Embeddedness and System Legitimacy

TPOM theory emphasizes that technology cannot function effectively in isolation; it must be embedded within organizational workflows. DIAP's integration into scheduling routines and daily briefings in both Australia and Bangladesh indicates a successful organizational fit.

Based on DIAP metrics, respondent A's statement were part of high-level operational meetings and planning discussions, making the tool both visible and legitimate. For Respondent B, its use in downtime tracking offered quantifiable evidence to justify maintenance interventions, which improved his credibility in communicating with upper management. This illustrates TPOM's point that legitimacy is constructed: systems become credible when their outputs align with internal priorities and hierarchies.

### 6.3.2 Interpersonal Practices and Informal Learning

The people dimension of TPOM was particularly evident in how users reported sharing knowledge. Both respondents described coaching others or being coached in using similar DIAP's dashboard features. This informal knowledge transfer created a distributed model of learning and problem-solving, consistent with techno-anthropological notions of embedded expertise.

These peer-to-peer practices also enabled localized customization. In Australia, shared dashboards were created for specific production lines; in Bangladesh, team members discussed which alert thresholds made sense based on machine age and ambient conditions. The system thus became a canvas for collaborative adaptation rather than a fixed tool.

### 6.3.3 Regional and Macro-Level Drivers

DIAP adoption was also influenced by regional and global trends. For example, Respondent A indicated that corporate alignment with Industry 4.0 strategies made DIAP's presence expected. In this environment, predictive analytics tools are becoming standard infrastructure. Respondent B's organization, while not operating in the same regulatory or technological ecosystem, still found value in DIAP as part of a modernization effort. The emphasis was on increasing uptime and meeting internal KPIs (key performance indicator).

These differences affirm TPOM's macroenvironmental component: different market pressures, industrial regulations, and maturity levels affect why and how PdM tools are adopted. The same dashboard is thus used to satisfy different narratives—efficiency in one case, modernization in another—revealing the socio-political embeddedness of industrial technologies.

## 6.4 Practical Implications

Several practical implications emerge:

- **Interface Design:** Designers should account for cross-cultural and cross-skill-level users. Systems should support multi-layered interaction, including basic mode for general users and advanced analytics for engineers.
- **Training and Onboarding:** Especially in regions or organizations with lower digital penetration, onboarding should include context-specific guides, peer learning strategies, and embedded support tools.
- **Organizational Integration:** Dashboard deployment should coincide with procedural embedding. This may include integrating dashboard metrics into review processes or aligning them with operational KPIs.
- **Strategic Alignment:** PdM tools should be framed not just as technical upgrades but as part of broader organizational or policy narratives (e.g., Industry 4.0 compliance, smart manufacturing).

## 6.5 Facing the Gaps:Challenges, Limitations and Future Opportunities

### 6.5.1 Challenges in Recruiting and Data Access

One of the study's major limitations was the limited sample size: only two Google Form responses were collected despite outreach via social media and email. This restricted the diversity of perspectives and limited the granularity of user-experience insights.

Furthermore, most empirical material came from public-facing DIAP documents, which, while informative, are naturally promotional. The absence of independent technical evaluations or critical internal reports limits triangulation.

### 6.5.2 The Road Not Taken: What More Interviews Might Have Revealed

Had more time and access been available, further insights could have been gained through:

- In-depth interviews for richer narrative data
- Observation of user-system interaction in live environments
- Comparative studies across different PdM vendors or industries

Such additions could deepen our understanding of variation across roles (operators vs. executives), sectors (food production vs. energy), and national contexts (developed vs. emerging economies).

### 6.5.3 Future Directions for Research and Practice

Future studies might:

- Explore PdM dashboard adoption across multiple continents and cultural-industrial contexts.

- Combine thematic analysis with ethnographic fieldwork for deeper socio-technical insights.
- Examine the long-term evolution of PdM practices, including resistance, adaptation, and reinterpretation.

## 6.6 Repositioning the Narrative: Synthesizing Insights Across Layers

The empirical findings by weaving together theoretical, practical, and contextual insights. Drawing from two distinctly situated users—a Maintenance Supervisor in Australia and an Engineer in Bangladesh—the discussion has revealed how PdM dashboards act as techno-organizational artifacts, shaping and shaped by their users.

By using HCI, TAM2, and TPOM, this chapter has framed PdM dashboards not merely as tools but as dynamic interfaces between people, machines, and institutions. Regional and organizational contexts have emerged as critical variables, affirming that successful technology adoption must be viewed as a situated, relational process.

# Chapter 7: Conclusion

The central aim of this thesis was to investigate the socio-technical dynamics involved in the implementation and usage of predictive maintenance (PdM) dashboards within industrial contexts. Specifically, the study employed three theoretical frameworks—Human–Computer Interaction (HCI), Technology Acceptance Model 2 (TAM2), and the Technology–People–Organization–Macroenvironment (TPOM)—to frame the analysis of both real-world industrial documentation and empirical user responses. These frameworks provided complementary lenses for understanding how PdM dashboards are designed, interpreted, adopted, and institutionalized in practice.

This research was carried out with a strong focus on techno-anthropological principles, emphasizing the situated, relational, and culturally embedded nature of technological adoption. Through the analysis of two distinct user responses—Respondent A from Australia and Respondent B from Bangladesh—and a thorough review of DIAP's predictive maintenance materials, the study has explored the human, technological, and organizational conditions that enable or hinder effective PdM dashboard integration.

## 7.1 Key Empirical Findings and Thematic Contributions

### 7.1.1 Usability and Human-Computer Interaction

A major contribution of this thesis lies in its nuanced analysis of usability under the HCI framework. The research revealed that while the DIAP dashboard presents a high degree of usability on the surface, user experiences diverge depending on prior exposure to digital systems, cultural familiarity with interface elements, and specific operational roles. Respondent A's seamless interaction with the dashboard contrasted with Respondent B's slower onboarding, illustrating how design must accommodate a range of cognitive models and skill levels.

The notion of layered learning emerged as a key design imperative. The study highlighted the importance of role-specific tutorials, embedded interface support, and culturally sensitive design metaphors as crucial elements for improving usability across contexts. This expands the conventional understanding of HCI in industrial systems, which often assumes homogeneous user bases and overlooks regional learning curves.

### 7.1.2 Acceptance and Behavioral Intention

Under the TAM2 framework, the research validated several key variables particularly perceived usefulness, ease of use, and subjective norms. Respondents consistently emphasized the strategic value of PdM dashboards in enabling timely interventions, preventing unplanned downtime, and supporting performance planning. However, these benefits were perceived and articulated differently across the two case contexts.

Respondent A viewed the dashboard as a decision-support tool within a digitally mature organization. For Respondent B, the dashboard offered immediate operational utility, especially in identifying equipment stress patterns. These variations emphasize the importance of aligning perceived usefulness with context-specific performance metrics. Moreover, social influence—especially managerial endorsement—was found to strongly influence adoption. This suggests that organizational support is not only a procedural requirement but also a cultural one, where expectations and legitimacy are communicated socially.

### 7.1.3 Organizational Embedding and Socio-Technical Integration

The TPOM framework helped uncover how PdM dashboards become normalized within the fabric of organizational life. Both respondents described changes in routine that accompanied with the introduction of DIAP, including new meeting structures, role-based data interactions, and informal learning communities. These findings underscore the techno-anthropological view that technologies are never static; they are adapted, negotiated, and repurposed within local settings.

Furthermore, macro-level drivers such as Industry 4.0 policy discourses and international competitive pressures shaped the strategic rationale for adopting PdM solutions. This macro-micro linkage is a critical insight: it demonstrates that technological adoption cannot be fully understood without examining broader institutional and market conditions.

## 7.2 Theoretical Contributions

This study contributes to the growing body of literature on industrial digitalization and user-centered technology adoption in several ways:

- **Extension of HCI Frameworks:** By applying HCI principles to the PdM dashboard context and contrasting user experiences from different regions, the research extends conventional usability analysis to consider layered cognitive, educational, and cultural diversity.
- **Contextualizing TAM2 Variables:** The study enriches TAM2 by emphasizing how perceived usefulness and social norms are shaped by institutional roles and industrial contexts, moving beyond individual intention to include structural enablers.
- **Operationalizing TPOM:** The TPOM framework proved instrumental in demonstrating the entanglement of technological, human, and organizational elements. This research operationalized the TPOM dimensions through concrete examples of PdM dashboard integration, providing a replicable template for future socio-technical studies.
- **Techno-Anthropological Depth:** The integration of techno-anthropology highlighted how PdM dashboards are not merely information systems but boundary objects that mediate between policy narratives, organizational routines, and human cognition.

## 7.3 Methodological Reflections

While the thematic analysis followed Braun and Clarke's six-phase approach rigorously, the empirical data was limited by a small sample size. With only two Google Form respondents and reliance on DIAP's internal documentation, the scope for generalization is necessarily constrained.

However, this limitation was partially offset by the depth of interpretive engagement and the triangulation of frameworks. The diversity between Respondent A and B offered a valuable comparative angle that aligned well with the techno-anthropological aim of situated analysis. The challenges encountered in data collection further underscored the practical realities of accessing industrial participants, especially within tight project timelines.

## 7.4 Future Research Opportunities

Building on the current study, future researchers can:

- **Scale up participant sampling** to include cross-functional teams from various countries and industries.
- **Adopt mixed-methods approaches** that combine surveys, interviews, and ethnographic observation.
- **Conduct longitudinal studies** to examine how PdM dashboard use evolves over time and how it interacts with broader digital transformation agendas.
- **Investigate ethical implications** such as decision-making automation, accountability, and worker autonomy within AI-assisted PdM systems.

By extending the empirical base and integrating interdisciplinary methods, future work can further deepen our understanding of predictive technologies as socio-technical systems.

## 7.5 Final Reflections

The complex terrain of predictive maintenance dashboards through a multi-theoretical, cross-cultural, and techno-anthropological lens. It has demonstrated that PdM dashboards are not passive tools but dynamic systems shaped by their technical design, user interactions, organizational embedding, and broader policy environments.

Ultimately, successful adoption depends on the alignment of system features with user needs, the presence of supportive organizational cultures, and the adaptability of technologies to diverse contexts. By centering both the technology and its users—across regions, professions, and infrastructures—this research contributes to a more inclusive and responsive understanding of industrial digitalization.

As digital transformation accelerates, such nuanced and grounded analyses will become increasingly vital for designing technologies that are not only functional but also meaningful, equitable, and sustainable.

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