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# Process-Specific Adoption of Predictive Maintenance: A Qualitative Comparative Analysis in Manufacturing

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**Abstract.** Predictive maintenance systems offer manufacturing enterprises opportunities to reduce costs and maximize productivity through data-driven insights into equipment failures. This study analyzes the adoption of predictive maintenance across six equipment assembly processes through an in-depth, multi-case methodology. Semi-structured interviews with maintenance managers elucidated nuances across processes contingent on vendor ownership models, facility lifecycles, and technical intricacy. Although processes evidenced expansions in predictive oversight through amplified data flows, persistent constraints arose regarding component lifespans, data limitations, and developing capable talent. Proactive management was partial rather than comprehensive. Strategic integration of robust failure mode analytics upgraded monitoring infrastructure, and bolstered personnel competencies will actualize the potential of predictive maintenance.

**Keywords:** intelligent manufacturing, maintenance system, predictive maintenance, preventive maintenance, failure analysis

# 1. Introduction

The repatriation of manufacturing industries to their home countries plays a pivotal role in rectifying the economic imbalances prevalent in developed nations, a phenomenon that has garnered substantial scholarly and policy attention. This resurgence has recently transformed into a prominent policy directive and a central strategy embraced by governments worldwide (Pegoraro et al. 2021). In addition, against the backdrop of an unparalleled era of fierce competition, characterized by the constant introduction of innovative products owing to the globalization of markets and shifting consumer preferences, the manufacturing sector is undergoing transformative changes. These changes entail a realignment of systems and functions in line with the integration of markets and resources. Intelligent manufacturing began to be used in earnest with the introduction of 'Industry 4.0' in 2011 after the smart factory was introduced in Kaiserslautern, Germany in 2006. Intelligent manufacturing transcends mere automation of manufacturing plants, as it entails a comprehensive integration of processes including product planning, design, production, distribution, and sales. This integration is rooted in information and communication technology, enabling the tailored production of goods with optimal cost-efficiency and swift turnaround times, achieved through the triad of automation, intelligence, and autonomy. This is defined as future manufacturing (Radziwon et al. 2014). The main technologies within intelligent manufacturing are primarily classified into applications, platforms, and devices, structured upon the principles of recognition, connection, and communication between objects used in the industry (Chen et al. 2018). The device represents the lowest-level hardware system, denoting a manufacturing apparatus that detects fundamental information encompassing physical, chemical, biological, and environmental attributes. It governs these aspects through real-time monitoring, analysis, and subsequent product generation.

For the continuous and effective operation of these devices and corresponding operating systems, a foundational requirement is a maintenance system comprising both technical and managerial components to fulfill necessary functions. Maintenance systems are continuously evolving with the development of related technologies, such as IoT, machine learning, and AI. The shift is from reactive management, which responds which responds to post-failure with a focus on mitigating failures, towards proactive management that minimizes loss costs, and improves efficiency by preemptively addressing unpredictable failures (Basri et al. 2017).

This study focused on a predictive maintenance system designed to optimize cost losses and efficiency by forecasting the occurrence of failures. This approach was built upon the backdrop of intelligent shifts within the manufacturing environment, the maintenance framework of devices, and the critical elements facilitating streamlined operation — a central area of focus. The primary inquiries include; first, the exploration of potential divergences in maintenance systems' strategic approaches and operational methods, contingent upon the distinctive attributes of the field and the existing level of development; second, an investigation into the influence of failure prediction and the management of actionable items, facilitated by data collection and analysis, on the expansion of predictive maintenance; and third, a comprehensive examination of the potential impact of professional manpower training and organizational culture on the optimization of facility maintenance systems.

The primary inquiries include: 1) exploring differences in maintenance approaches based on field attributes; 2) investigating the influence of failure prediction and corrective measures facilitated by data analysis on expanding predictive maintenance; and 3) examining the impact of human capabilities and organizational culture on optimizing maintenance systems. The remainder of this paper is structured as follows. In Chapter 2, the theoretical foundation is established by delineating the definition and purpose of the maintenance system, followed by a thorough analysis of the current status, challenges addressed through case analyses at each evolutionary stage, and the distinctions and limitations that arise from the specific characteristics and environmental contexts of each industry. In Chapter 3, the core factors that increase the completeness and application rate of the maintenance system are examined through multiple case studies on the maintenance system within various fields, concurrently presenting the methodology employed. In Section 4, the main results obtained through multiple case studies are summarized, and in Section 5, the conclusions and implications are presented.

## 2. Literature Review

The manufacturing industry's reliance on interconnected technology fosters real-time interaction between individuals, machinery, and data, positioning it as the epicenter and nucleus of the fourth industrial revolution, transitioning from automation to intelligence and autonomy (Kim & Shim, 2019, Xu et al. 2018, Zadeh, 2021). Intelligent manufacturing, underpinned by real-time data analysis from controlled facilities such as robots and sensors through wireless links (e.g., quality enhancement, outlier monitoring, and cloud platforms), is the core of value creation (Namjoshi & Rawat, 2022). Equipment maintenance refers to a series of processes that preserve the state of equipment so that the equipment can continuously maintain their original function. This maintenance is categorized into three types: Reactive Maintenance (RM), Preventive Maintenance (PM), and Predictive Maintenance (PdM). Equipment maintenance is currently evolving along with the latest technologies such as internet of things (IoT), sensing technology, and Artificial Intelligence (AI) (Chen et al, 2017, Compare et al, 2020). RM entails restoring original functionality post-failure in a reactive manner, striving to reinstate operation after substantial downtime and facing limits on escalating post-repair costs. In addition, losses owing to unplanned equipment outages have been extensively studied. Notably, Amazon's experience highlights the magnitude of losses, with a mere 49-minute equipment outage resulting in a staggering loss of over four billion USD. Correspondingly, the Ponemon Institute reports an average loss of 170 million USD per hour due to sudden failures (Ran, 2019). This underscores the mounting significance of proactive management that preempts failures. PM, a proactive strategy, is executed before failures manifest and adheres to a predetermined schedule based on time intervals or process repetitions, consequently enhancing replacement efficiency and cost-effectiveness. Beyond averting failures and issues, PM extends equipment lifespans. Moreover, optimizing maintenance through the periodic and systematic presentation of failure probabilities and predictive models from equipment events or log data constitutes a significant domain (Bakdi et al. 2022). It is crucial to maintain PM limits within the scheduled framework to circumvent premature, costly replacements. As these challenges persistently grow, the need to predict and proactively manage impending failure points through advanced facility condition monitoring intensifies. However, there are limitations due to obstacles such as a lack of qualified personnel and inadequate data infrastructure (Wang, 2019).

Because PdM is based on facility status information, it can realize the original goal of maximizing the availability of production systems while minimizing maintenance costs (Zonta et al. 2020). Regardless of PdM or PdM 4.0, the paradigm is continuously evolving. This evolution rests upon the premise of hyperconnectivity, which harnesses the potential of core technologies such as the IoT, Big data, machine learning, and AI, and is analyzed by remote monitoring and failure in advance to anticipate and take actions. Because the amount of information that can be obtained from the production system is rapidly increasing owing to IoT, big data, and machine learning, it is being used to propose maintenance scenario applications based on data obtained from IoT sensing devices or to present a manufacturing framework based on big data. These studies are oriented toward cost-wise innovation (Civerchia et al. 2017, Kumar et al. 2018). Furthermore, an investigation was conducted into a machine learning-based model designed to identify potential data that could indicate defects within the system, ultimately resulting in the proposal of a predictive model for estimating remaining life with the aim of reducing maintenance costs. However, this study has its limitations, as it is limited to a case study of a specific process, such as a radial fan, and it needs to be assessed whether it can be equally applicable to other processes like sophisticated semiconductor processes (Zenisek et al. 2019). Through various research endeavors like these, diverse methodologies are being employed to explore Predictive Maintenance (PdM). However, while it is possible to enhance the accuracy of analysis using sensors and big data, the goal of achieving an automated maintenance system still faces limitations, as data quality remains unchanged (Maktoubian et al. 2021).

As described above, fault recognition and analysis technologies have been studied in many previous studies on PdM. However, organizational problems, such as problems occurring from the user's perspective and business changes in actual manufacturing sites, are constantly occurring. Therefore, to introduce PdM, problems affecting users and interorganizational factors must be considered first. In line with this, a framework was proposed from the perspectives of organizational culture, decision-making, supply chains, and cooperation based on interviews with 13 experts in asset management and predictive analysis (Golightly et al. 2017). In the strategic aspect, high-level decision-makers focus on cost, whereas practitioners focus on practical value. Decision-making must be grounded in IT acumen garnered from solution development and maintenance. In addition, training courses and costs are necessary, and cooperation for competency development, such as through education centers, is required. Based on research on the components to be considered for the application of PdM, a more detailed analysis is required from the execution perspective, encompassing professional personnel engaged in facility maintenance, competency development training, leadership aptitude, and cooperative investments.

# 3. Research Methodology

## 3.1. Multiple case study method

The research method used in this study is a multi-case analysis method, focusing on the main processes within the manufacturing industry to which PdM, which collects and analyzes data based on facility conditions and the facility maintenance system, is applied. A case study is a qualitative research methodology that collects and analyzes data on a specific case from a theoretical perspective. This approach can perform a realistic and specific analysis, affording the opportunity to compare the commonalities and uniqueness across cases (Massaro et al. 2019). In addition, owing to the imperfect implementation and constant evolution of facility maintenance systems, obtaining statistically significant results is challenging. In order to thoroughly analyze the maintenance status and limitations of ongoing, evolving processes that are not yet fully completed, a case study methodology was chosen. Additionally, a multiple-case methodology was chosen to supplement the specific localized analysis results and to analyze the specificity and environment of each process. Above all, through direct case studies in actual processes, it was possible to conduct substantial validation, including problem identification and strategic analysis, addressing the limitations previously presented in prior research. Additionally, to ensure objectivity and consistency in the investigation process, interviews, reports related to facility maintenance, and maintenance-related indicators were used to supplement subjective elements.

This study has limited its scope to the electronic component manufacturing industry, which is considered a foundational technology in various industrial sectors. There are two main reasons for this choice. First, this industry is known for driving economic growth by producing the smallest and most sophisticated products, which involves high technological complexity and the application of diverse processes. Second, it is a field that pursues the implementation of data-driven smart factories for performance enhancement and quality control. For the purpose of conducting case studies that reflect various process situations and equipment characteristics, this paper considerd technical specifications and precision requirements based on the representativeness of equipment companies, company responsiveness, equipment service life, equipment price, and equipment complexity. To address the limitation of being specific to particular situations, six processes were selected to represent each item. By conducting case analyses on six out of the main eight processes, excluding two similar processes, we ensured comprehensive coverage. Furthermore, reports and production metrics representing accuracy and reliability for each process were used as references. Interviews were conducted, taking into account current responsibilities and key experiences to minimize errors focusing on certain areas and to provide direction for the final objectives and strategies. Table 1 provides an overview of the subjects and the current status of Predictive Maintenance (PdM) analysis in this study. Interviews were conducted with manager-level individuals who have experience in processes beyond their current responsibilities for one~two hours, in addition to their total career experience and current positions, to mutually compensate for the subjectivity and limited data. Particularly, the application status of PdM for the target processes consists of three essential elements: defining component lifespans, applying various intelligent functions to new equipment, and equipment-related knowledge. The difficulty of implementing PdM is attributed to the lack of historical data for components or failures in all processes. This is often due to manual documentation that varies depending on the author, and in many cases, it does not accurately depict the causality of failures.

Figure 1 illustrates the flowchart of the method employed in this study. Initial steps involved defining the case analysis subject and methodology, along with preparing the interview questionnaire. Subsequently, comprehensive interviews were carried out, considering process variations and statuses. The result was then subjected to analysis. Owing to the interview-based nature of the case study, it commenced by introducing the study's purpose, assessing mutual understanding to establish standardized agreement and criteria for each case.

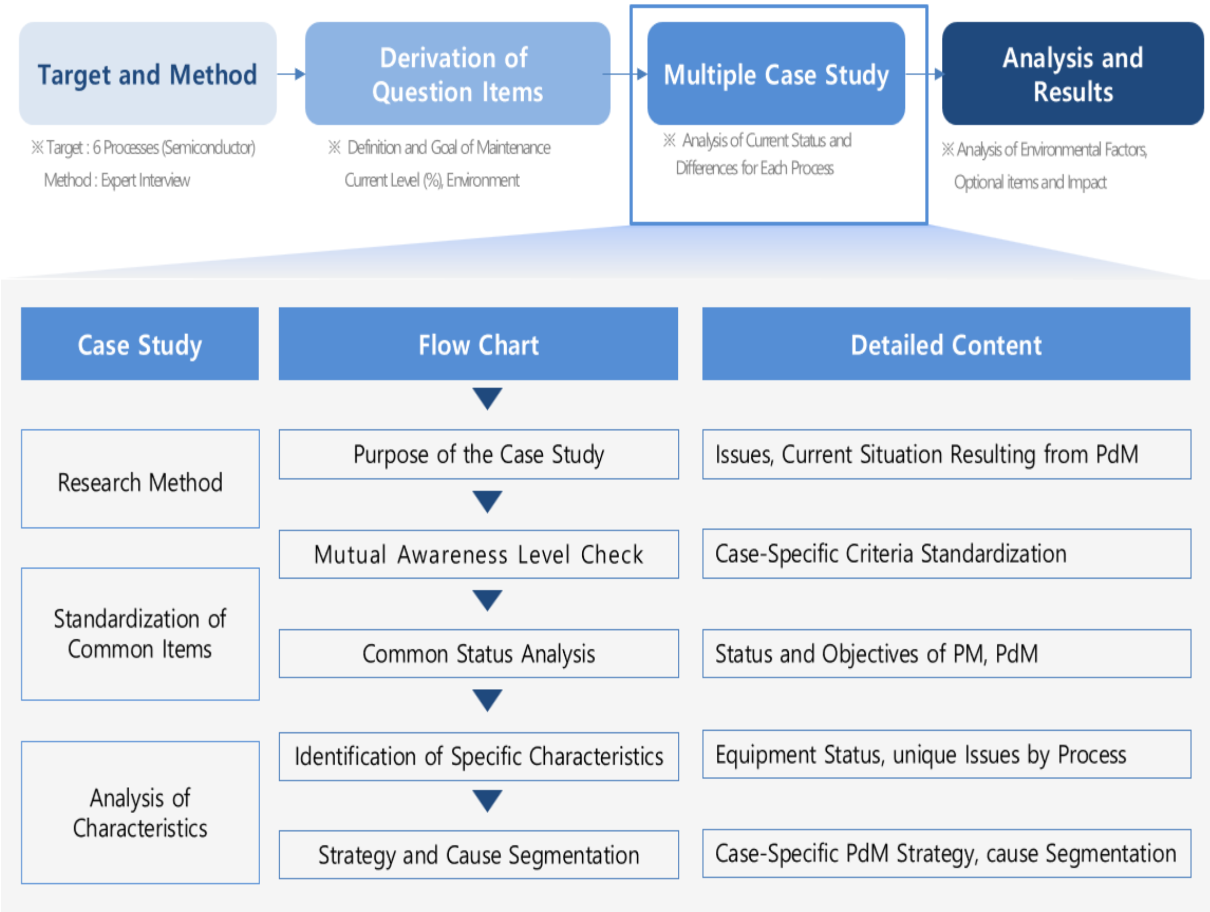


Fig. 1: Methodology for case studies and flowchart

Table 1: Overview of multiple case studies

| Target Process | Interviewees | | | PdM Prerequisites | |
|---|---|---|---|---|---|
| | Career | Position | Experience in Other Processes | Essential Elements | Challenges |
| A Process | 20 years | 2nd Level Manager | Possessing relevant experience | Defining Lifespans for Individual Components | Insufficient component and failure history database |
| B Process | 22 years | 1st Level Manager | Possessing relevant experience | Defining Lifespans for Individual Components | Insufficient component and failure history database |
| C Process | 26 years | 1st Level Manager | Possessing relevant experience | Defining Lifespans for Individual Components | Insufficient component and failure history database |
| D Process | 17 years | 2nd Level Manager | Possessing relevant experience | Need for new smart equipment | Insufficient component and failure history database |
| E Process | 15 years | 2nd Level Manager | Possessing relevant experience | Equipment-related knowledge | Insufficient component and failure history database |
| F Process | 15 years | 2nd Level Manager | Possessing relevant experience | Equipment-related knowledge | Insufficient component and failure history database |

## 3.2. Research model

This study began with questions aimed at identifying the challenges and key factors that need to be addressed in order to apply the practical results of existing prior research related to the core technologies and procedures of maintenance system evolution and predictive maintenance in real-world settings. Figure 2 outlines the research model's schematic diagram, scrutinized from three viewpoints: (a) examining the existing state of facility maintenance systems in actual processes, encompassing facility possession status and process-specific technology; (b) exploring each stage's pivotal technology as per the PdM Process Flow, entailing a sequence of steps for data collection, analysis, and decision-making; and (c) analyzing the personnel training, investment, and collaboration system, grounded in proficient manpower and the organizational structure executing facility maintenance tasks.

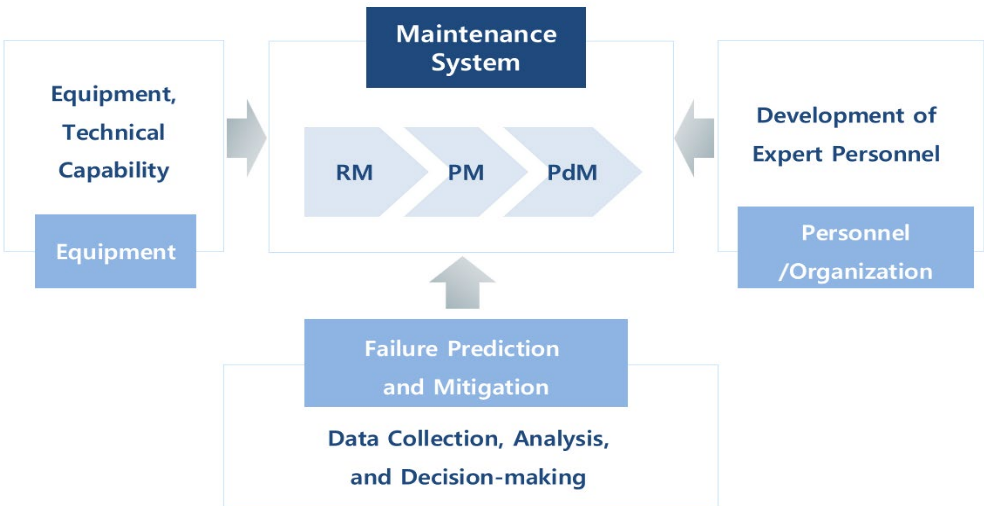


Fig. 2: Research model

# 4. Results

## 4.1. Facility holding status and field attributes

Facility maintenance and maintenance systems are developed to enhance efficiency from CM, post-management, to PM and PdM. However, these systems do not uniformly evolve. They incorporate various elements based on industry and process-specific facility statuses, failure predictions, measures, professional workforce, and organizational structure. Even with advanced PdM, elusive or long-term emerging failures persist, demanding ongoing follow-up management.

The first research inquiry of this study is that maintenance strategies evolve differently depending on the field conditions. Therefore, an analysis was conducted on the attributes and characteristics of the field that influence this. As a result, it was confirmed that factors affecting equipment maintenance extend beyond direct factors such as equipment specifications or precision, and also include regional issues both domestic and international, as well as the responsiveness of companies and pricing. The outcomes of the facility status analysis in the case study process were juxtaposed with facility firms, their responsiveness, and the duration of facility ownership and costs (Table 2). Company responsiveness denotes the time taken to address facility-related issues. Response times of three days were categorized as good, one week as moderate, and any longer as poor. Responsiveness was closely tied to ownership duration, with shorter ownership periods correlating to better responsiveness, particularly with newer facilities. The interviewee from Process C stated, "In Process C, the main equipment is from a local domestic company, and due to the long equipment ownership period and lack of new investments, the company's priority for this process is low, resulting in a subpar responsiveness." Facility cost did not exert a significant impact. Regarding equipment retention periods, the relative value between processes was integrated alongside the actual retention time. For instance, if equipment has a retention period of three years and a new model emerges, this model may not be owned. However, it could be present in other process equipment. If retention extends beyond five years, the process's retention period is deemed low. In the case of processes A and D, having the shortest facility ownership duration, a represented a domestic facility company, while D stood for an overseas company. Regardless of this distinction, both exhibited good responsiveness. Concerning process F, akin to process A in terms of holding time and equipment cost, the company's responsiveness was weak. This was attributed to disparities between domestic and foreign companies. Accessibility and easy communication with practitioners favored domestic firms, while foreign ones often relied on domestic agents, leading to substantial response delays during similar events.

Moreover, when intricate equipment specifications and extended retention periods converged, companies' response capabilities were diminished. Specifically, complex requirements, exemplified by process C's long retention period, yielded low responsiveness even for a domestic company. The intricacy of requirements corresponds to the proficiency level of responding firms; however, limitations persist in securing experienced and capable manpower. Particularly at the working level, retaining experts proves challenging owing to job transitions.

Table 2: Analysis of equipment maintenance

| Target Process | Business Responsiveness | Vendor | Ownership Period | Price | Specifications | Precision requirements |
|---|---|---|---|---|---|---|
| A Process | Great | Domestic | Short | High-priced | Complex | High |
| B Process | Good | Domestic | Average | Moderately-priced | Simple | Moderate |
| C Process | Poor | Domestic | Long | Moderately-priced | Complex | Moderate |

| | | | | | | |
|---|---|---|---|---|---|---|
| D Process | Great | Overseas | Short | Low-priced | Simple | High |
| E Process | Good | Overseas | Long | High-priced | Moderate | High |
| F Process | Poor | Overseas | Short | High-priced | Complex | High |

## 4.2. PdM-based facility failure prediction and action

It determined that all six processes subjected to multiple-case analysis are evolving in terms of their equipment maintenance systems. The basis for this assessment is the increasing rate of predicting and managing failures in advance. In other words, the interplay of real-time data acquisition from processes and equipment, as addressed in the second research inquiry, has an impact on the expansion of predictive maintenance through failure prediction and corrective measures. While there exist notable disparities in the number of management elements for both PM and PdM across processes (Table 3), all experienced growth when linked to the aforementioned facility status. The positive correlation between company responsiveness and the rise in the number of pre-managed elements is generally apparent. Foreign companies, despite lower responsiveness, establish a foundation for addressing global clientele, resulting in an augmented count of pre-managed elements irrespective of their responsiveness.

PdM is founded on data analysis derived from equipment state monitoring, encompassing data collection, analysis, and fault action phases. In the data collection phase, experts for each process partitioned collected data into direct data from manual temperature or pressure measurements via sensors and facility data such as logs or work-related events. Although a surge in direct data obtained via manual measurements led to a moderate rise in pre-management items, the growth was subdued when facility data remained consistent. Among processes A, B, C, and D, characterized by increased direct data, the least pronounced surge in pre-management items was observed in processes B and C. This can be attributed to constraints in real-time monitoring of direct data. First, despite smart sensor technology, applying it to equipment with lengthy retention periods posed spatial and technical challenges that hindered universal utilization, except in special cases directly tied to quality assurance, limiting its scope. Second, affixing new sensors to aged facilities incurs substantial indirect expenses, encompassing system development and memory upgrade costs for data operation, thus serving as an investment deterrent. The manager of Process C, which has the longest retention period, stated, "Adding new features to the current equipment is quite challenging. This is because there is limited space for mounting new sensors on the equipment, and improving software for data collection and analysis is not feasible. The cost of developing customized software for some customers is too high compared to the equipment price. Therefore, from the equipment's perspective, developing new equipment with these features for global customers is considered reasonable for both the company and the customers," explaining the difficulties. Finally, analyzing causal relationships proves complex due to misalignment between data collection intervals, operational periods, and facility timeframes. Nevertheless, even in instances where direct data analysis didn't surge, processes E and F witnessed an upswing in pre-management items as equipment data, inclusive of equipment logs and event analyses, expanded. This progress demands minimal investment since only system enhancements are required sans hardware modifications, facilitating tailored data collection aligned with facility operational segments.

Table 3: Analysis of failure prediction

| Target Process | Number of Pre-Maintenance Items | Data collection | | Data analysis | | Fault Remediation | |
|---|---|---|---|---|---|---|---|
| | | Direct data | Equipment data | Visualization | Analysis | Replacement | Root cause analysis |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| A Process | Increased significantly | Increase | Increase | Increase | Increase | Increase | Increase |
| B Process | Increased slightly | Increase | Same | Same | Same | Same | Same |
| C Process | Increased slightly | Increase | Same | Same | Same | Same | Same |
| D Process | Increased moderately | Increase | Same | Same | Increase | Same | Same |
| E Process | Increased moderately | Same | Increase | Increase | Increase | Increase | Increase |
| F Process | Increased moderately | Same | Increase | Increase | Increase | Increase | Increase |

Visualization of the collected data demonstrated a direct correlation with an escalated rate of linkage analysis. Regarding visualization, foreign companies exhibited a more pronounced connection analysis aspect, particularly in catering to global customers. Additionally, an increase in collected facility data directly led to visualization, serving as a foundation for subsequent data analysis. When data collected through this method were visualized, scalability tended to improve through linkage analysis. Processes with heightened linkage analysis witnessed an increase in pre-management items, often reaching a middle or higher level. Measures like vision-based quality monitoring within the facility or facility operation were proposed for validation purposes. The data gathered and analyzed pertained to the identification of failures and the deterioration of individual components, directly influencing part replacement and failure cause analysis. Facility data and part replacement were closely interrelated and followed a parallel pattern. The depth of data analysis was directly linked to cause analysis within the context of visualization. In processes A, E, and F, where visualization was extensive, the ease of part replacement and cause analysis was heightened. Nonetheless, in scenarios where facility specifications were straightforward and company responsiveness was high, advanced data analysis was feasible. Consequently, even with a secured foundation for linkage analysis, substantial growth in relation to failure management was not consistently observed.

## 4.3. Human competency analysis results

Lastly, one of the most crucial aspects in a manufacturing setting, whether it's after a breakdown or before, is the actual replacement and repair of components. Thus, we confirmed that key factors include the presence of specialized personnel who directly carry out these tasks, skills development, and organizational culture. Particularly, differences and specificities in each case, such as the status of specialized personnel and automation in each process, were found to have an impact. To analyze the organizational culture, such as professional personnel directly performing facility maintenance, competency development training, and collaboration with companies, part analysis and maintenance execution status were confirmed (Table 4). Part information and history management were negatively correlated with the failure rate, which was low when part information or history management was high. Process A had high part information and a medium level of history management; compared to other processes, the current status of part analysis was high and the factory ratio was the lowest compared to other processes. In addition, part information and history management generally showed positive correlations. This is because history management is difficult if no information is available about the parts, and the failure rate was also high. In the case of foreign companies, there was no place with high part information, which was found to be less responsive than domestic companies owing to security issues. In addition, it was confirmed that history management was limited in cases where knowledge of part information was low, even though the failure rate was high, despite having many experience points.

Table 4: Status of Component Analysis and Maintenance Execution

| target process | component analysis ratio | | | maintenance status | | |
|---|---|---|---|---|---|---|
| | Component information | Failure rate | History management | Core functionality | Simple replacement | Vendor |
| A Process | High | Low | Medium | In-house experts | In-house experts | On-site |
| B Process | Low | High | Low | External experts | In-house experts | Off-site |
| C Process | Low | High | Low | External experts | In-house experts | Off-site |
| D Process | Medium | Medium | Low | In-house experts | In-house experts | On-site |
| E Process | Medium | Medium | Low | External experts | External experts | Off-site |
| F Process | Low | High | Low | External experts | In-house experts | Off-site |

The subsequent analysis focuses on practitioners engaged in facility maintenance, categorized by mechanical components, core functional elements with direct quality impact, and straightforward replacements based on facility parts. Furthermore, practitioners are classified into company experts and internal staff. Concerning mechanical components, regardless of the process, company experts held responsibility due to the infrequent occurrence of breakdowns. This role demands comprehensive knowledge about the entire facility structure. In the realm of core functions, processes with extensive parts information, like process A, were overseen by designated individuals. Meanwhile, process D exhibited a moderate level of parts information but had uncomplicated facility specifications, leading to the designated individual taking charge. Conversely, for all other processes with limited parts information, company experts managed facility maintenance and core functional aspects. For tasks involving simple replacements, all processes except process E were managed by designated staff members. In the case of process E, equipment status verification was necessary even for simple replacements. Minor deviations hold significant consequences for product quality, mandating thorough checks after each operation.

Competency development training, leader competency and collaboration, and investment competency exhibit correlations with the duration of facility ownership and price. Facility competency training was executed through practical field education, encompassing both theoretical knowledge and hands-on facility operations. Foreign companies maintain resident manpower or experts through domestic branches, thus ensuring immediate on-site response capability. A unique aspect emerged in light of COVID-19 restrictions, leading to limitations on on-site and group education. Consequently, video and online education for the same processes progressively gained traction. Notably, differences arose in education approaches for new recruits and experienced workers. New recruits primarily engaged in hands-on field learning, given their need to acquaint themselves with equipment for the first time. Conversely, experienced workers, often constrained by time, underwent intermediate and advanced training online. A growing emphasis was observed in cultivating experts proficient in data collection and analysis for PdM, alongside hardware specialists skilled in equipment parts replacement across all processes. Because of this, tailored training programs were integrated to meet these demands.

# 5. Discussion

The most fundamental message obtained through this study, which is a multiple-case analysis, is that there is a unanimous consensus that maintenance is evolving from traditional post-maintenance to predictive maintenance (PM and PdM). All six interviewees from the various processes mentioned the importance of proactive management in both PM and PdM. Proactive management involves predicting the timing of equipment downtime and planning maintenance systematically, rather than simply comparing costs and time. They emphasized that the key lies not only in cost efficiency through accurate data-based analysis like PdM but also in establishing a self-controllable system. They stated, "Even though RM may be efficient from a total cost perspective in terms of component unit cost and quantity, our process is evolving towards proactive management that can control issues in advance, and predictive maintenance (PdM) is the strategic direction.". However, it was acknowledged that not all components can be managed solely through proactive maintenance due to factors such as long failure cycles exceeding two to three years or unpredictable failures related to critical parts like mechanical components. Therefore, a mixed approach is often adopted. The reason for this mixed approach lies in the difficulty of predicting failures for all components. Therefore, beyond utilizing AI, IoT, and real-time data acquisition, as in previous research, there is a need to apply these technologies in real manufacturing environments and establish decision-making strategies. As one of these methods, this study analyzed the construction of a database for critical components in actual manufacturing environments, rather than attempting to predict failures for all components. Critical components are those that directly impact product quality and equipment reliability, and the emphasis was on building a database of component information and failure history for these critical components. Additionally, recent developments have proposed and implemented methods for equipment self-awareness, automatic cleaning, and replacement.

The most fundamental prerequisite for proactive maintenance is awareness of the lifespan of each component. Optimization of proactive management operations is deemed necessary based on this information. However, defining the lifespan is challenging for all six processes for three main reasons. First, when defects or failures occur, it is difficult to establish clear cause-and-effect relationships and intuitive, consistent analyses of quality impacts due to multiple interdependencies. Second, existing failure histories are not well-documented, making it difficult to use them as a basis for setting intervals or conducting root cause analyses. Third, even for identical components, variations in performance can arise based on the supplier and price selected by the equipment manufacturer, making it impossible to confirm and database this information in advance. From a technical perspective, in addition to defining the lifespan, it was noted that current technology is lacking or that there is a shortage of practical experts in equipment and data. For example, while sensors for measuring temperature, time, and force are available, pressure measurement sensors either do not exist or are prohibitively expensive for practical use.

Equipment specialists' capabilities vary depending on the specifications and functions of individual equipment, and significant differences were observed based on opportunities and experience in the field. In particular, data analytics requires an understanding not only of the data but also of the characteristics of the process and the composition of the equipment. Therefore, developing experts in this field is challenging. To address these limitations, they were collaborating with companies to establish systematic online and offline training programs. Furthermore, in some processes, they were utilizing external experts to enable operations even in the absence of in-house experts. Therefore, the expertise in equipment maintenance was not only based on individual capabilities but also occurred organizationally through collaborative efforts and organizational culture.

# 6. Conclusion

This study analyzed previous research on the components and evolution of equipment maintenance systems. Based on this, it conducted a study on factors that influence actual manufacturing processes, with a focus on semiconductor assembly processes, through multiple-case analysis of six distinct processes. The core areas of equipment maintenance in actual manufacturing processes can be categorized into three as follows, and several factors within each area have been confirmed to influence the current maintenance status and strategy development.

Firstly, equipment maintenance encompasses not only direct factors such as equipment specifications or precision but also indirect factors like vendor affiliation, region, current ownership periods, pricing, and more. Secondly, in the evolution of the current equipment maintenance systems, the key aspect regarding the transition from PM to PdM is the ability to predict and manage failures in advance based on data, which impacts the expansion of PdM. Lastly, it was confirmed that experts who perform tasks such as component replacement, along with the educational system to nurture them and inter-organizational collaboration, are the key influencing factors. Through multiple cases, we analyzed the key influencing factors, the challenges in each process, and the optimized maintenance strategies for each situation. This study differentiates itself from previous research that primarily focused on case studies of specific components or processes within a limited context based on methodologies like the Internet of Things and machine learning. Instead of being confined to specific components, it employs a multiple-case analysis to thoroughly examine the specificities of each process and address real-world challenges. Building on this analysis, it provides guidance for the strategic expansion of equipment maintenance systems. Finally, as a future task, in pursuit of the fundamental goal of cost optimization, it is impractical to implement PdM in all components and processes. Therefore, research is needed for an integrated strategy for equipment maintenance, focusing on optimal management ratios and algorithms. The logic proposed in the future will provide a logical and consistent framework for the overall process and will offer optimization solutions based on environmental analysis results such as case studies of individual processes.

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