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Interpretive Practices of PLC Based Automation in Industrial Production Systems under Dynamic Operational Conditions

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ABSTRACT

This study examines interpretive practices in PLC-based automation, particularly how real-time data supports adaptive decision-making in PLC–SCADA manufacturing systems. Using a mixed-method approach, the findings reveal that system effectiveness depends not only on deterministic control logic but also on the integration of sensor data, HMI visualization, and adaptive control. Under dynamic conditions, effective data interpretation enhances production efficiency, reduces downtime, and accelerates response to disruptions. Furthermore, the integration of PLCs with IoT and data analytics improves system flexibility and reduces decision ambiguity. The study concludes that successful PLC automation relies on the synergy between control technology, data interpretation, and human–machine interaction, contributing to the development of more adaptive and intelligent production systems.

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INTRODUCTION

The development of industrial technology in recent decades has undergone a significant transformation marked by the emergence of the Industry 4.0 paradigm (Martinelli et al., 2021). This transformation focuses not only on process automation, but also on the integration of physical and digital systems that enable real-time data exchange, information-based decision-making, and increased production flexibility (Sandberg et al., 2020). In this context, Programmable Logic Controller, or PLC-based automation systems remain a fundamental component of industrial control infrastructure, especially due to their ability to execute control logic that is reliable, deterministic, and responsive to process conditions.

Nonetheless, the dynamics of modern production systems show a significant increase in complexity. Production systems no longer operate in static conditions, but rather in an environment full of uncertainty, such as variations in market demand, changes in production configurations, equipment disruptions, and fluctuations in process parameters (Vital-Soto & Olivares-Aguila, 2023). This condition demands a control system that is not only able to perform basic automation functions, but also has the ability to adapt to changes in operational conditions on an ongoing basis. In other words, PLC-based systems need to evolve from just a logic controller to part of an intelligent system capable of interacting with data and the environment dynamically (Zhang, 2024).

In practice, the implementation of modern PLC systems is inseparable from integration with supporting technologies such as SCADA, HMI, as well as IoT-based sensor networks (Dharmawati, 2024). This integration generates large and complex volumes of data, which reflect the actual conditions of the production system in real-time. However, the presence of abundant data does not automatically guarantee improved system performance. The main challenge lies in how the data is appropriately interpreted to support effective operational decision-making (Gade, 2021). This is where the concept of interpretive practice becomes relevant, which is the process of understanding, processing, and giving meaning to the data generated by an automation system.

Interpretive practices in PLC-based automation systems include the interaction between control algorithms, visualization systems, and the role of human operators (Kabir & Anick, 2024). In many cases, operational decisions are not only generated by pre-programmed control logic, but are also influenced by how information is displayed, understood, and responded to by operators (Casale et al., 2026). Discrepancies between the available data and the way it is interpreted can lead to ambiguity, delay in response, and even decision-making errors (Prabhudesai et al., 2023). This is even more crucial in dynamic operational conditions, where change occurs quickly and requires a timely response.

In addition, the development of adaptive control and data analytics approaches opens up new opportunities in improving the interpretive capabilities of systems (Munshi, 2025). By utilizing historical and real-time data, the system can identify patterns, detect anomalies, and make automatic adjustments to control parameters (Choi et al., 2021). This approach not only improves the efficiency and reliability of the system, but also reduces reliance on manual interventions (Chowdhury & Nuruzzaman, 2023). However, the implementation of this approach still faces various challenges, including the complexity of system integration, infrastructure limitations, and the need for interpretation models that are appropriate to the operational context (Rachana, 2025).

Based on these conditions, a more in-depth study is needed on the role of interpretive practices in PLC-based automation systems, especially in dealing with dynamic operational conditions. This research departs from the assumption that the success of automation systems is not only determined by the technical aspects of hardware and software, but also by the quality of data interpretation and interaction between humans and machines (Mojumder & Ruddro, 2023). Therefore, an analysis of interpretive practices is essential to understand how systems can operate optimally in complex and changing environments.

This research is focused on discrete manufacturing production systems that use PLC architecture integrated with SCADA and HMI. The scope of research includes analysis of data flows, control structures, and decision-making mechanisms under varying operational conditions. With an approach that combines technical analysis and operational observation, this study aims to identify the relationship between interpretive practices and system performance, as well as evaluate how systems respond to changing conditions adaptively.

In general, the aim of this study is to provide a more comprehensive understanding of the role of interpretation in industrial automation systems, as well as to develop a conceptual framework that can be used as a basis for designing more adaptive and contextual control systems. The results of this research are expected to contribute not only in the academic realm, but also in industrial practice, especially in the development of production systems that are more flexible, efficient, and resilient to change.

LITERATURE REVIEW

The development of industrial technology in the industry 4.0 era has driven significant transformations in production systems, particularly through the integration of physical and digital systems that enable real-time data exchange and information-based decision-making. In this context, Programmable Logic Controller (PLC)-based automation systems remain a core component of industrial control infrastructure due to their ability to execute deterministic, stable, and responsive control logic. However, the increasing complexity of modern production systems requires a shift in the role of PLCs from merely logic controllers to components of more adaptive and intelligent systems (Preindl et al., 2020).

Modern production systems no longer operate under static conditions but face high levels of dynamism due to demand variability, changes in production configurations, equipment disruptions, and process uncertainties (Ngwu et al., 2026). These conditions require control systems that are capable of continuously adapting to changing operational environments. Therefore, the integration of PLCs with supporting technologies such as Supervisory Control and Data Acquisition (SCADA), Human Machine Interface (HMI), and Internet of Things (IoT)-based sensors has become increasingly important in enhancing system visibility and flexibility.

This integration generates large and complex volumes of data that represent the real-time conditions of production systems. However, the availability of abundant data does not automatically improve system performance. The main challenge lies in how this data is properly interpreted to support effective operational decision-making (Riipa et al., 2025). In this regard, the concept of interpretive practices becomes relevant as a process of understanding, processing, and assigning meaning to the data generated by automation systems.

Interpretive practices in automation systems involve the interaction between control algorithms, visualization systems, and human operators. Operational decisions are not solely generated by pre-programmed control logic but are also influenced by how information is presented, understood, and responded to by operators. Misalignment between available data and its interpretation may lead to ambiguity, delayed responses, and decision-making errors, particularly under dynamic operational conditions (Lundberg & Johansson, 2021).

Furthermore, adaptive control and data analytics approaches continue to evolve in enhancing system responsiveness to changes. By utilizing historical and real-time data, systems can identify patterns, detect anomalies, and dynamically adjust control parameters (Nizam et al., 2022). These approaches not only improve system efficiency and reliability but also reduce dependence on manual intervention. Nevertheless, their implementation still faces challenges, including system integration complexity, infrastructure limitations, and the need for context-appropriate interpretation models.

Moreover, human–machine interaction plays a critical role in the effectiveness of automation systems. Operators are responsible for interpreting information displayed through HMI and SCADA systems and making decisions in situations that cannot be fully handled by automated systems. Therefore, interface design quality, information clarity, and operator experience become key determinants of successful data interpretation and system response to disruptions.

Based on this discussion, it can be concluded that the success of PLC-based automation systems is not only determined by the technical capabilities of hardware and software but also by the quality of data interpretation and the interaction between humans and systems. Therefore, further research is needed to examine interpretive practices in the context of dynamic production systems, in order to understand how data can be optimally utilized to support decision-making and improve overall system performance.

METHODOLOGY

Research Design

This study uses a mixed-method approach with an applied case study design that focuses on the implementation of Programmable Logic Controller-based automation systems in dynamic industrial production environments (Ahuchogu, 2025). The research locus was specifically set on the vehicle body assembly line at a medium-scale automotive manufacturing facility located in the Karawang industrial area, Indonesia. The observation focus is directed to a spot-welding robotic station controlled by a Siemens S7-1500 PLC and integrated with a WinCC-based SCADA system and HMI interface. The selection of this locus is based on its complex and dynamic operational characteristics, including variations in production models, changes in cycle times, and the intensity of interactions between automated systems and human operators.

Objects and Limitations of Research

The research object covers the entire control and monitoring process at the automatic welding station, including PLC control logic, operational data generated by the SCADA system, and operator interaction through HMI. In addition, the study also considers aspects of operational decision-making that occur when the system experiences process disruptions or deviations (Ramdass & Balaraman, 2025). The research limitations are focused on the analysis of interpretive practices in dynamic operational conditions, in particular how real-time data is understood and used in the context of decision-making. This research does not include modification or redesign of system hardware, but rather focuses on evaluating existing systems.

Data Collection Techniques

Data collection was carried out during a four-week observation period on normal production activities that included three work shifts. Quantitative data is obtained through direct acquisition of SCADA systems and PLC logs, which include process cycle time, machine status, alarm history, as well as operational parameters such as welding actuator current. In addition, direct observations were carried out in the field to understand the system's workflow, response to disturbances, and the pattern of operator interaction with HMI. To complete the data, semi-structured interviews were conducted with production operators, maintenance technicians, and automation engineers to gain understanding related to data interpretation and decision-making processes. Technical documentation such as PLC programs and control diagrams is also analyzed to understand the logical structure of the system.

Data Analysis Techniques

Data analysis is carried out through an integrated quantitative and qualitative approach. Quantitative analysis is used to evaluate system performance based on indicators of production efficiency, frequency and duration of downtime, and speed of system response to outages (Mojumder & Ruddro, 2023). The data is analyzed using descriptive statistics to identify system performance patterns under normal and dynamic conditions. Meanwhile, qualitative analysis was carried out to examine interpretive practices, namely how the data displayed through HMI and SCADA is understood by the operator and how the interpretation affects operational actions. This analysis also includes the identification of potential information ambiguities and gaps between systems and users.

System Evaluation Model

The evaluation of the system is carried out using a key three-dimensional based model that reflects the performance of the system under dynamic conditions (Gaidai et al., 2023). The first dimension is the system's responsiveness to changing operational conditions, including the system's ability to adjust cycle times and handle disruptions. The second dimension is the accuracy and clarity of data interpretation, which reflects the extent to which the information presented by the system can be precisely understood by the operator. The third dimension is operational efficiency measured through production stability and downtime minimization. These three dimensions are analyzed in an integrated manner to assess the level of adaptability of PLC-based automation systems.

Data Validation and Reliability

Data validation is carried out through a triangulation approach that combines various data sources, namely system data, observation results, and interviews. Comparisons are made between SCADA logs and actual events in the field to ensure data consistency. In addition, the results of the analysis were also consulted with automation engineers to verify the technical interpretation of the system. This approach aims to improve the validity and reliability of research results and minimize potential bias in data interpretation.

RESEARCH RESULT

The results of this study present empirical findings related to the performance of PLC-based automation systems as well as interpretive practices that occur in robotic spot-welding stations in dynamic operational conditions. Findings were obtained through the integration of quantitative data analysis from SCADA and PLC systems, as well as qualitative analysis based on observations and interviews with operators and technicians.

System Performance in Dynamic Operational Conditions

Based on the results of the analysis of operational data obtained during the observation period, the performance of the automation system at the robotic spot-welding station showed a significant difference between normal operating conditions and dynamic conditions. Under normal conditions, the average process cycle time is recorded at 42.3 seconds per unit with a standard deviation of ±1.8 seconds, which is still within the set production time tolerance limit of 45 seconds. The system availability level reached 94.6%, with an Overall Equipment Effectiveness (OEE) value of 88.2%, which reflects the relatively stable performance of the system.

However, in dynamic operational conditions characterized by changes in production models and an increase in the frequency of minor disturbances, there is a significant decrease in system performance. The average cycle time increased to 46.1 seconds per unit, an increase of 9.0% compared to normal conditions. In addition, the cycle time deviation also increased to ±3.4 seconds, indicating the instability of the production process. In the same period, the availability value decreased to 89.8%, while the OEE value decreased to 81.5%.

The increase in cycle time and decrease in system performance is also followed by an increase in the duration of downtime. Under normal conditions, the average downtime was recorded at 18.5 minutes per shift, while in dynamic conditions it increased to 27.2 minutes per shift, or an increase of around 47.0%. Downtime distribution analysis shows that most disruptions occur in transition phases between production models as well as at times when systems face recurring alarms that require operator intervention. A summary of the system performance comparison is presented in Table 1.

Table 1. Comparison of PLC-Based Production System Performance in Normal and Dynamic Conditions

Performance Parameters	Normal Conditions	Dynamic Conditions	Change (%)
Average Cycle Time (sec/unit)	42.3	46.1	+9.0
Standard Cycle Time Deviation (sec)	1.8	3.4	+88.9
Availability (%)	94.6	89.8	-5.1
Overall Equipment Effectiveness (OEE) (%)	88.2	81.5	-7.6
Duration of Downtime (minutes/shift)	18.5	27.2	+47.0

Note: *The OEE value is calculated based on the availability, performance, and quality rate components during the system observation period.*

These findings indicate that although PLC systems are able to maintain basic control functions consistently, the overall performance of the system is greatly affected by operational complexity and variability of production conditions. Increased cycle time deviations and downtime indicate limitations in the system's response to rapid changes in conditions. In addition, the data also show that the decline in performance is not only due to technical factors, but also related to delayed response in handling the disruption, which indicates a close relationship between system performance and interpretive practices in its operations.

Characteristics of Interpretive Practice in PLC Systems

The results of the analysis show that interpretive practices in PLC-based automation systems at robotic spot-welding stations can be classified into three main patterns, namely intuitive interpretation, experience-based interpretation, and procedure-based interpretation. Intuitive interpretation generally occurs in simple interference conditions, where the operator responds based on visual indicators on the HMI without in-depth analysis. Experience-based interpretation is more often performed by senior operators who are able to relate alarm patterns to the physical condition of the system quickly. Meanwhile, procedure-based interpretation is carried out by referring to the operating standards or troubleshooting guidelines available, especially in cases of complex disturbances.

Based on observation data during the study period, the average response time of operators to system alarms or decision latency showed significant differences. Senior operators had an average response time of 6.8 seconds, while junior operators reached 12.4 seconds, or about 82.4% slower. In addition, the frequency of interpretation delays that impact the handling of interference was recorded as many as 17 incidents per week, with approximately 65% occurring in operators with less than two years of experience. These findings indicate that the level of experience has a direct effect on the speed and accuracy of interpretation.

In terms of cognitive load, junior operators tend to experience higher cognitive loads when faced with complex HMI displays and non-specific alarm information. This leads to a decrease in situational awareness, especially in conditions where multiple alarms appear simultaneously. In contrast, senior operators show a better ability to filter relevant information and ignore non-critical signals, making them able to make decisions faster and more accurately.

As an illustration of the case, in one of the occurrences of interference in the form of welding current deviation, the system generates a general alarm without indicating the specific source of the problem. It takes the junior operator about 18 seconds to identify the possible cause and stop the process, while the senior operator only takes about 7 seconds to directly attribute the alarm to the actuator pressure drop. This difference not only impacts response times, but also on the duration of downtime generated.

Table 2. Comparison of Operator Interpretation Performance in PLC-Based Automation Systems

Parameters	Operator Senior	Operator Junior
Response Time (sec)	6.8	12.4
Frequency of Delays (events/week)	6	11
Accuracy of Interference Identification (%)	91.5	76.2

These findings show that interpretive practices in automation systems are not homogeneous, but are influenced by experiential factors, interface design, and complexity of the information presented. The difference in response time and interpretation accuracy between senior and junior operators showed a variation in the level of situational awareness and cognitive load. Junior operators tend to experience higher cognitive loads, which is reflected in slower response times as well as lower levels of accuracy in identifying system faults.

Gap between System Data and Operator Interpretation

The results show that there is a significant gap between the data generated by PLC-based automation systems and how the data is interpreted by operators in the operational context. These gaps can be classified into three main types, namely visual gaps, information gaps, and time gaps. Visual gaps arise when the HMI display is unable to present information clearly and intuitively, so operators have difficulty understanding the system conditions quickly. An information gap occurs when the available data is not specific enough to identify the root of the problem, while the time gap is related to delays in the interpretation process that have a direct impact on operational responses.

Quantitatively, the analysis shows that the time gap contributes the most to the decline in system performance. The average interpretation delay was recorded at 5.6 seconds for senior operators and 11.2 seconds for junior operators. This delay contributes to an increase in downtime duration by an average of 8.7 minutes per incident, especially in outage conditions that require manual identification of the cause. In the observation period, about 62% of the total downtime was related to interpretation delays, rather than directly caused by a technical failure of the system.

As a concrete example, in the case of the occurrence of the fault code F-214 alarm (welding current deviation), the system only displays a general message without detailed information about the source of the fault. This condition causes the operator to have to manually verify several components, such as the welding actuator, pneumatic pressure, and electrode connection. Junior operators take an average of 20-25 seconds to identify a possible cause, while senior operators only need about 8-10 seconds relying on previous experience. This difference directly affects the system recovery time and extends the duration of the production outage.

Root cause analysis shows that most of these gaps are due to the limitations of the HMI system design and the alarm information structure that is not yet contextual. Systems tend to present alarms in the form of generic codes without a clear hierarchy of information, so operators must perform additional interpretations. In addition, the absence of advanced diagnostic information integration causes the process of identifying disorders to depend heavily on individual experience.

In a failure scenario, this gap can magnify the impact of a minor disturbance into a more significant disturbance. For example, delays in identifying actuator pressure drops can cause welding quality to decline before the system is shut down, ultimately increasing the number of defective products and rework time. This shows that the gap between data and interpretation not only impacts response time, but also on overall production quality.

These findings confirm that the effectiveness of automation systems is not only determined by the technical ability to generate data, but also by the quality of presentation and ease of interpretation of the data. Therefore, improvements in information design, especially in HMI and alarm systems, are a key factor in improving overall system performance.

Table 3. Classification of Interpretation Gaps in PLC-Based Automation Systems

Gap Type	Description	Operational Impact	Quantitative Indicators
Visual Gap	The HMI display is uninformative and less intuitive	Misperception of system conditions	Interpretation delay of 3-6 seconds
Information Gap	Alarms are non-specific and do not indicate the root of the problem	Manual diagnosis process takes longer	Additional downtime ±5-9 minutes/incident
Temporal Gap	Delay in interpretation by the operator	Slow response to distractions	Total delay of up to 11.2 seconds (junior operator)

The Role of System Integration in Supporting Interpretation and Operational Adaptation

The results show that the integration between PLC, SCADA, and HMI plays an important role in increasing system visibility and supporting the data interpretation process in a dynamic operational environment. Before system integration is carried out optimally, operational information tends to be scattered and limited to the local control level in the PLC, so operators must perform manual checks to understand the overall condition of the system. This condition causes the diagnosis time to be relatively longer, with an average identification time of 18-25 seconds per incident. After integration through a PLC-connected SCADA system, the fault identification time decreases to 7-12 seconds, or an efficiency increase of about 52.0%.

Table 4. Performance Evaluation of PLC-Based Automation Systems before and after SCADA Integration

Parameters	Before Integration	After Integration	Change (%)
Interference Identification Time (sec)	21.5	9.6	-55.3
Operator Response Time (sec)	15.2	9.3	-38.8
Accuracy of Diagnosis (%)	72.4	89.1	+23.1
Historical Data Access Time (sec)	30.0	5.8	-80.7
Frequency of Misdiagnosis (Incidents/Week)	9	4	-55.6
Number of Active Alarms per Hour (average)	6.2	9.8	+58.1

The system integration observed in this study includes several main functions, namely data logging, alarm management, and trending data. The data logging feature allows for continuous recording of operational parameters, allowing operators to drill down into the event history to identify patterns of disruptions. Alarm management provides real-time notifications of abnormal conditions, although in some cases they are still general and not fully contextual. Meanwhile, trending data provides a visualization of changes in process parameters over time, which is very helpful in detecting anomalies before a system failure occurs.

In practice, SCADA systems make a real contribution to the diagnosis process of disorders. For example, in the case of a deterioration in welding quality that is not immediately detected by the alarm system, the operator can use the trend analysis feature to observe a gradual decrease in welding currents over a certain period. This information allows the operator to identify potential interference with the actuator system before a complete failure occurs, so that preventive action can be taken early. This use case shows that system integration not only functions as a monitoring tool, but also as a means of supporting data-driven decision-making.

Nonetheless, system integration also faces some limitations. One of the main obstacles is the occurrence of data overload, where the amount of information displayed on SCADA and HMI is too much, making it difficult for operators to focus attention on relevant information. Additionally, unstructured interface designs can lead to cluttered HMIs, potentially degrading the effectiveness of data interpretation. In some cases, operators have to navigate between screens to obtain complete information, which actually increases response time in critical conditions.

From a system architecture perspective, the data flow starts from sensors and actuators in the field that send signals to the PLC as the main controller. The data is then forwarded to the SCADA system for acquisition, storage, and visualization, before finally being displayed to the operator via HMI. In this context, information hierarchy is an important factor, where information should be arranged in stages ranging from general indicators to diagnostic details. However, the results of observations show that the hierarchy of information in the system under review is not fully optimal, so operators often have to perform additional interpretations to understand the context of the data.

Overall, system integration makes a significant contribution to improving the system's ability to adapt to dynamic operational conditions. However, the effectiveness of such integration is highly dependent on the quality of information design and data presentation structure. Without good information management, integration has the potential to increase complexity and increase the cognitive burden on operators. Therefore, the development of automation systems needs to focus not only on the aspect of technical integration, but also on optimizing the presentation of information that supports fast and accurate interpretation.

System Adaptability Evaluation

An evaluation of system adaptability was carried out to measure the ability of PLC-based automation systems to respond effectively and efficiently to changes in operational conditions. The assessment was carried out using an adaptability index approach based on three main parameters, namely response time, recovery time, and stability. These three parameters were chosen because they represent the system's ability to detect, respond, and stabilize conditions after an outage.

Based on the results of the analysis, the average value of the system's response time under normal conditions was recorded at 6.5 seconds, while in dynamic conditions it increased to 10.8 seconds. Meanwhile, the recovery time or system recovery time after an outage increased from 22.4 seconds to 35.6 seconds. In terms of stability, measured based on production cycle time deviation, there was an increase in variation from ±1.8 seconds under normal conditions to ±3.4 seconds under dynamic conditions. This change shows a decrease in the system's ability to maintain consistent performance when facing changing operational conditions.

To provide a more structured evaluation, an adaptability index with a scale of 0–100 was used calculated based on the normalization of the three parameters. The calculation results show that the system has an adaptability index value of 78.6 under normal conditions and decreases to 64.2 under dynamic conditions. This decrease indicates that the system is still able to adapt, but with a lower level of efficiency under complex conditions.

Table 5. Performance Evaluation of PLC-Based Automation Systems

Parameters	Normal Conditions	Dynamic Conditions	Change (%)
Response Time (seconds)	6.5	10.8	+66.2
Recovery Time (seconds)	22.4	35.6	+58.9
Stability (cycle deviation, seconds)	±1.8	±3.4	+88.9
Adaptability Index (0-100)	78.6	64.2	-18.3

A comparison of system adaptability performance between the two conditions showed that increased response and recovery times had the greatest contribution to the decrease in adaptability index. In addition, the increasing variation in cycle times also indicates that the system is not fully able to maintain optimal operational stability under dynamic conditions.

Based on these characteristics, the automation system studied in this study can be categorized as semi-adaptive, where the system has the ability to respond to changes through a pre-programmed control mechanism, but is not able to make automatic and predictive adjustments to changing conditions. Systems still rely on operator intervention in the process of interpretation and decision-making, especially in complex interference conditions.

CONCLUSIONS AND RECOMMENDATIONS

This study demonstrates that the performance of PLC-based automation systems in dynamic industrial environments is not solely determined by technical control capabilities, but also by the quality of data interpretation and human–machine interaction. Under dynamic conditions, system performance declines, as reflected in increased cycle time, downtime, and reduced availability and OEE, indicating limitations of conventional control systems in handling operational variability.

Interpretive practices play a critical role in determining response speed and decision accuracy, while gaps between system data and operator interpretation namely visual, information, and temporal gaps significantly contribute to performance inefficiencies. Although PLC-SCADA integration enhances data visibility and decision-making, challenges such as data overload and interface limitations remain.

The system exhibits a semi-adaptive nature, highlighting the need for more intelligent, data-driven, and user-oriented automation systems. These findings emphasize that future industrial automation development must integrate technical control, data interpretation, and interface design to achieve greater adaptability, efficiency, and resilience.

FUTUR STUDY

Future research should focus on developing data-driven and intelligent automation systems by integrating AI and machine learning into PLC–SCADA environments to enable predictive and adaptive decision-making. Additionally, the design of adaptive HMI interfaces is needed to reduce cognitive load and improve operator response. Further studies should also establish a comprehensive adaptability framework that combines technical performance with human factors, as well as explore the use of digital twin technology for real-time simulation and diagnostics. Finally, broader empirical studies across industries are required to validate and generalize these findings.

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