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Physics-Informed AI and Digital Twin Framework for Real-Time Predictive Maintenance and Energy Optimization of Hydrogen-Integrated Industrial Systems

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Abstract

Hydrogen-integrated industrial systems combine electrolyzers, compressors, storage units, pipelines, heat exchangers, and power-electronic equipment with digital sensing, control, and energy-management infrastructures, creating operating environments in which equipment degradation, process stability, and energy consumption develop together rather than independently. Existing research has examined physics-informed artificial intelligence, digital twins, real-time industrial data, predictive maintenance, and energy optimization largely as separate technical streams, leaving limited quantitative evidence on how these capabilities jointly relate to integrated maintenance and energy performance. This study developed and empirically evaluated a physics-informed AI and digital twin framework grounded in Cyber-Physical Systems Theory, specifying Physics-Informed AI Capability (PIAIC), Digital Twin Integration Capability (DTIC), Real-Time Industrial Data Intelligence (RTIDI), Predictive Maintenance Intelligence Capability (PMIC), and Energy Optimization Intelligence Capability (EOIC) as predictors of Predictive Maintenance and Energy Optimization Performance (PMEOP). A quantitative, explanatory, cross-sectional, case-study-based survey design was employed. Of 320 structured five-point Likert questionnaires distributed to maintenance, process, automation, energy, AI, and managerial professionals across hydrogen, refining, power, steel, and industrial-gas settings, 289 valid responses were retained (90.3%). Reliability and validity were satisfactory (Cronbach's α = .85–.92; KMO = .894; Bartlett's test $p < .001$; 72.4% cumulative variance explained). Pearson correlations between PMEOP and all five predictors were positive and significant ($r = .67–.78$, $p < .001$). Multiple linear regression explained 73.2% of the variance in PMEOP (adjusted $R^2 = .727$; $F(5, 283) = 154.63$, $p < .001$), with EOIC (β = .31), PMIC (β = .27), DTIC (β = .23), PIAIC (β = .20), and RTIDI (β = .17) each retaining significant unique effects ($p < .001$) and no multicollinearity concerns (VIF = 1.67–1.92). All five hypotheses were supported. The findings indicate that maintenance and energy performance in hydrogen-integrated systems is associated with the coordinated maturity of physically grounded intelligence, synchronized virtual representation, real-time data, maintenance reasoning, and energy-oriented decision-making rather than with any single technology, offering an empirically validated basis for integrated cyber-physical asset management.

Keywords

Physics-informed artificial intelligence; Digital twin; Predictive maintenance; Energy optimization; Hydrogen-integrated industrial systems; Real-time industrial data intelligence; Cyber-physical systems

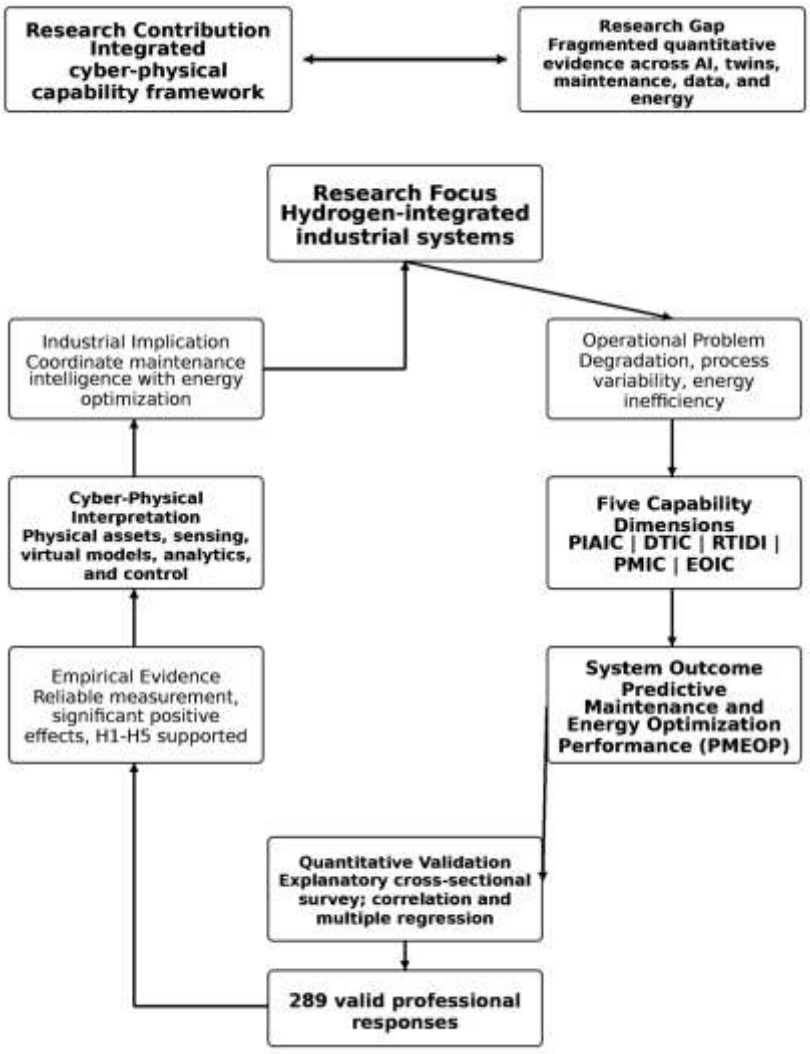
INTRODUCTION

Hydrogen-integrated industrial systems can be understood as interconnected industrial configurations in which hydrogen production, conditioning, compression, storage, distribution, conversion, and end-use processes interact with conventional production equipment, energy-management systems, sensing infrastructure, and process-control technologies. Hydrogen functions simultaneously as an energy carrier, industrial feedstock, storage medium, and process input, which gives it relevance across refining, ammonia and fertilizer production, chemicals, steelmaking, power systems, and other energy-intensive applications (Staffell et al., 2019; Veras et al., 2017). Water electrolysis provides a particularly important pathway because it links electrical energy directly with hydrogen production through electrochemical conversion. In "Hydrogen Production From Water Electrolysis" (pp. 410-426), electrolyzer performance has been related to electrical input, conversion efficiency, operating conditions, and integration with wider energy systems (Ursúa et al., 2012). Proton-exchange-membrane electrolysis has further demonstrated how current density, cell voltage, temperature, pressure, membrane characteristics, catalyst performance, and water quality collectively influence hydrogen production and equipment behavior (Carmo et al., 2013; Pervaz, 2026). Comparative analysis of hydrogen-production pathways has also shown that energy and exergy efficiency, resource requirements, environmental characteristics, and process configuration strongly affect technical performance (Dincer & Acar, 2015). These characteristics make hydrogen-integrated industrial systems dynamic physical environments in which equipment health, process stability, and energy performance develop together rather than independently. Real-time knowledge of temperature, pressure, flow, current, voltage, vibration, hydrogen purity, output, and energy consumption therefore becomes essential for understanding actual system condition. The technical complexity of these systems also creates a need for analytical approaches that can combine process knowledge with high-frequency industrial data instead of treating hydrogen equipment as a collection of disconnected assets (Kumar & Himabindu, 2019).

Predictive maintenance has become central to advanced industrial asset management because it shifts maintenance decisions from predetermined intervals toward evidence derived from the observed condition and expected degradation of equipment. In "A Review on Machinery Diagnostics and Prognostics Implementing Condition-Based Maintenance" (pp. 1483-1510), condition-based maintenance has been organized around data acquisition, data processing, diagnostics, prognostics, and maintenance decision-making, establishing a clear analytical chain between measured equipment behavior and maintenance intervention (Jardine et al., 2006). Machinery-health prognostics has subsequently expanded this logic by linking condition signals with degradation assessment and remaining-useful-life estimation (Lei et al., 2018; Mst Shamima, 2026). Machine-learning approaches have strengthened predictive maintenance by learning health indicators and failure patterns from large and heterogeneous equipment datasets, although their effectiveness depends on representative observations, meaningful features, suitable prediction horizons, and model stability under changing operating regimes (Carvalho et al., 2019; Susto et al., 2015). Industry 4.0 research has further connected predictive maintenance with sensors, industrial connectivity, digital infrastructures, asset monitoring, and automated analytical systems (Mallioris et al., 2024; Zonta et al., 2020). These requirements become particularly demanding in hydrogen-integrated facilities because compressors, pumps, electrolyzers, storage units, pipelines, power electronics, heat exchangers, and auxiliary systems may experience interacting mechanical, thermal, electrical, electrochemical, and fluid-dynamic degradation. A change in pressure, current, vibration, temperature, or energy demand may represent normal operational variability, a deliberate process transition, or an early indication of deterioration. Maintenance intelligence must therefore distinguish expected physical behavior from abnormal behavior while preserving sufficient sensitivity for early fault detection. This problem also connects maintenance with energy performance because degraded equipment can consume additional energy, reduce conversion efficiency, disturb process stability, and increase operational cost. Predictive maintenance in hydrogen-integrated systems consequently requires an analytical structure that represents both asset condition and energy-related consequences.

Physics-informed artificial intelligence provides a technically grounded approach for combining machine learning with scientific and engineering knowledge. In "Physics-Informed Neural Networks" (pp. 686-707), physical differential equations have been incorporated into deep-learning procedures so that model training accounts for governing system behavior while solving forward and inverse problems (Kanti, 2026; Raissi et al., 2019). The broader physics-informed machine-learning paradigm has integrated observed data with mathematical physics, boundary conditions, conservation relationships, and domain knowledge in settings where measurements may be noisy, sparse, incomplete, or high dimensional (Karniadakis et al., 2021; Rony & Md, 2026).

Figure 1: Overall Physics-Informed AI and Digital Twin Research Framework



This approach differs from purely data-driven artificial intelligence because a model does not have to infer every system relationship solely from historical examples. Physics-guided recurrent learning has demonstrated how prior scientific knowledge can constrain predicted states and improve physical consistency when observations are limited (Jia et al., 2021), while heat-transfer applications have shown that sparse measurements can be combined with governing equations to estimate temperature and velocity fields under uncertain conditions (Cai et al., 2021). Informed machine learning has also been categorized according to the source, representation, and point of integration of prior knowledge, including equations, simulations, rules, and structural constraints (von Rueden et al., 2023). Integrated physics and machine-learning models have therefore emerged as hybrid analytical systems rather than substitutes for either physical modeling or statistical learning (Seyyedi et al., 2024). This principle is

directly relevant to hydrogen-integrated industrial assets because mass balance, energy conservation, pressure-flow relationships, heat transfer, electrochemical reactions, equipment degradation, and operating limits provide established knowledge that can accompany sensor data. Physics-Informed AI Capability in this study has consequently represented the organizational and technical capacity to integrate such knowledge into monitoring, diagnosis, prediction, and optimization so that data-driven outputs remain connected to physically credible industrial behavior.

Digital twins extend this physical-data integration by maintaining virtual representations of industrial assets, processes, or systems that are linked with their physical counterparts. In "Digital Twin in Manufacturing" (pp. 1016-1022), digital twins have been distinguished from static digital models and one-directional digital shadows through the degree of automated data integration between physical and virtual entities (Kritzinger et al., 2018). A functional digital twin therefore requires more than simulation because the virtual representation must remain sufficiently synchronized with changing physical conditions to support monitoring, analysis, prediction, or control. Digital-twin architectures have been closely associated with cyber-physical systems because both depend on computation, communication, sensing, and physical process interaction, while the twin provides an explicit virtual representation of asset state and behavior (Khalid, 2026; Tao et al., 2019). Manufacturing research has linked digital twins with production planning, process monitoring, big-data analytics, and predictive maintenance (Qi & Tao, 2018), and application reviews have identified monitoring, maintenance, optimization, management, and safety among important digital-twin services (Cimino et al., 2019). Characterization studies have emphasized physical entities, virtual entities, state information, measurement, and bidirectional physical-virtual connections as central elements of digital-twin systems (Jones et al., 2020; Mashfiqur, 2026). Their implementation has additionally depended on industrial Internet of Things connectivity, artificial intelligence, data analytics, cloud or edge computing, and interoperable information infrastructures (Fuller et al., 2020). Maintenance-focused studies have shown how digital twins can support degradation monitoring, diagnosis, maintenance planning, and condition-based decision support (Errandonea et al., 2020; Dinter et al., 2022). Hydrogen technologies have also been represented through data-driven digital twins, including high-temperature proton-exchange-membrane electrolyzer models that combine multiphysics simulation, system identification, thermal dynamics, hydrogen generation, and power-consumption behavior (Zhao et al., 2022).

Industrial energy optimization has increasingly become connected with real-time data, digital representations, artificial intelligence, and equipment-health information because energy consumption is produced by interacting process and asset conditions rather than by isolated loads. In "Recent Advances on Industrial Data-Driven Energy Savings" (Article 110208), sensor information, digital infrastructures, artificial intelligence, and digital twins have been linked with industrial energy monitoring and energy-saving decisions (Mashiat, 2026; Teng et al., 2021). Hydrogen production further illustrates this integration because operating conditions determine both energy performance and equipment stress. Machine-learning-based optimization of steam-methane-reforming hydrogen production has demonstrated that data-driven models can represent complex process relationships and search operating spaces subject to engineering constraints (Lee et al., 2021; Kaium, 2026). The existing literature nevertheless remains fragmented across several technical streams. Physics-informed AI research has primarily emphasized physically consistent prediction and scientific modeling, digital-twin research has emphasized synchronized virtual representation and lifecycle services, predictive-maintenance research has emphasized condition assessment and failure prediction, and hydrogen studies have often concentrated on production technologies, degradation, safety, or efficiency. This fragmentation leaves limited quantitative evidence explaining how Physics-Informed AI Capability, Digital Twin Integration Capability, Real-Time Industrial Data Intelligence, Predictive Maintenance Intelligence Capability, and Energy Optimization Intelligence Capability relate simultaneously to an integrated maintenance and energy-performance outcome in hydrogen-integrated industrial systems. The present study has addressed this empirical gap by specifying these five technological capabilities as independent constructs and Predictive Maintenance and Energy Optimization Performance as the common dependent construct. The resulting framework has allowed the study to evaluate how physical knowledge, real-time sensing, virtual-system representation, maintenance intelligence, and

energy optimization have been associated within one cyber-physical industrial architecture, thereby maintaining direct correspondence among the research title, hypotheses, measurement model, and quantitative analysis.

Background of the Study

Hydrogen-integrated industrial systems have increasingly been characterized by the close interaction of physical equipment, energy-conversion technologies, real-time sensing infrastructures, computational models, artificial intelligence, and automated decision-support mechanisms (Aditya & Ahmed, 2022; Asheke & Maksudul, 2022; Asheke & Badrul, 2022). These systems may include electrolyzers, compressors, pumps, hydrogen storage units, pipelines, heat exchangers, power-electronic components, control systems, and associated industrial machinery operating within interconnected production environments (Akter & Sumaiya, 2022; Imran & Jannatul, 2022; Maksudul & Islam, 2022). Their performance has depended not only on the reliability of individual assets but also on the ability of the complete system to maintain stable operating conditions while controlling energy consumption, equipment degradation, process variability, and maintenance requirements (Morshedul & Islam, 2022; Stabak & Shahid, 2022; Feroz & Pervaz, 2022). Conventional maintenance approaches based primarily on predetermined schedules or reactive intervention can be inadequate in such environments because equipment deterioration may develop under complex and continuously changing thermal, mechanical, electrical, electrochemical, and fluid-dynamic conditions (Islam & Md, 2023; Asheke, 2023; Feroz & Shabbir, 2022). Predictive maintenance has provided a more data-oriented approach by using equipment-condition information to identify abnormal behavior, anticipate failures, estimate degradation, and support timely maintenance decisions (Shahid, 2023; Islam & Ahmed, 2023; Sadia & Mosheur, 2023). At the same time, energy optimization has become closely connected with maintenance performance because deteriorating equipment can consume additional energy, reduce hydrogen-production efficiency, disturb process stability, and increase operating costs (Adnan, 2024; Islam, 2024; Ashik, 2024). Artificial intelligence has expanded the ability of industrial systems to process large volumes of operational data, although purely data-driven models may generate predictions that are difficult to reconcile with known engineering behavior when data are sparse, noisy, incomplete, or collected under changing operating regimes (Kynatun & Saba, 2024; Maksudul, 2024; Shahid, 2024). Physics-informed artificial intelligence has provided a more technically grounded approach by incorporating physical laws, engineering constraints, conservation relationships, process equations, and domain knowledge into AI-supported prediction and optimization (Islam, 2024; Sumaiya, 2024; Taher et al., 2024). Digital twins have further strengthened this analytical environment by creating dynamically updated virtual representations of physical assets and processes that can receive real-time information, simulate operating states, evaluate degradation, and support maintenance and energy-management decisions (Ashik, 2025; Kynatun, 2025; Mostari, 2025b). The integration of physics-informed AI, digital twins, real-time industrial data intelligence, predictive maintenance analytics, and energy optimization has therefore created an interconnected framework in which the physical state of hydrogen-related assets can be continuously interpreted through both engineering knowledge and operational data. This research has examined these capabilities as measurable organizational and technological constructs and has evaluated their relationships with predictive maintenance and energy optimization performance in hydrogen-integrated industrial systems (Masrul, 2025; Maksudul, 2025; Shahriar, 2025).

Problem Statement

The operation of hydrogen-integrated industrial systems has presented a complex maintenance and energy-management problem because equipment reliability, process efficiency, hydrogen production, energy consumption, and operational safety are strongly interconnected (Shahid, 2025; Islam, 2025; Sadia, 2025). Hydrogen-related equipment may experience degradation caused by temperature variations, pressure fluctuations, mechanical wear, electrochemical deterioration, material stress, contamination, load cycling, component aging, and changes in operating conditions (Ashik, 2026; Shabbir, 2025; Sadmeen, 2025). When these changes are not identified sufficiently early, they can contribute to reduced equipment availability, inefficient energy use, unplanned interruptions, increased maintenance requirements, unstable process conditions, and lower overall system

performance (Hasib, 2026; Kynatun, 2026; Mostari, 2026). Conventional preventive maintenance systems frequently depend on fixed inspection intervals and historical schedules, while traditional data-driven predictive models may rely heavily on correlations extracted from past observations without explicitly considering the physical rules governing hydrogen processes and industrial equipment (Hasinur, 2026; Maksudul, 2026; Mohsin, 2026). This has created a methodological limitation because statistically accurate patterns do not always represent physically plausible operating conditions. Digital twins can provide real-time virtual representations of industrial systems, yet their effectiveness depends on continuous data synchronization, accurate modeling, analytical intelligence, and the ability to translate virtual-system information into operational decisions (Shahriar, 2026; Shahid, 2026a, 2026b). Existing approaches have often examined artificial intelligence, digital twins, predictive maintenance, industrial data analytics, and energy optimization as separate technical areas. As a result, there has remained insufficient integrated quantitative evidence explaining how these capabilities collectively influence maintenance and energy performance in hydrogen-integrated industrial environments (Sadia, 2026; Shabbir, 2026; Sumaiya, 2026). There has also been limited empirical understanding of whether physics-informed AI capability, digital twin integration capability, real-time industrial data intelligence, predictive maintenance intelligence capability, and energy optimization intelligence capability make distinct contributions to an integrated performance outcome (Sadmeen, 2026; Umme, 2026). The research problem addressed in this study has therefore been the absence of a statistically validated framework that connects these technological capabilities with predictive maintenance and energy optimization performance within hydrogen-integrated industrial systems. Addressing this problem has required a structured quantitative investigation in which the relevant capabilities have been operationalized as measurable constructs and their individual relationships with system performance have been evaluated through descriptive analysis, correlation analysis, and multiple regression modeling.

Purpose and Objectives of the Study

The purpose of this study has been to develop and quantitatively evaluate an integrated physics-informed artificial intelligence and digital twin framework for improving real-time predictive maintenance and energy optimization performance within hydrogen-integrated industrial systems. The study has specifically sought to determine how different technological and analytical capabilities have contributed to the ability of industrial organizations to identify equipment deterioration, interpret operational conditions, support maintenance decisions, optimize energy use, and improve the integrated performance of hydrogen-related industrial assets. The first objective has been to examine the relationship between Physics-Informed AI Capability and Predictive Maintenance and Energy Optimization Performance by assessing the extent to which engineering principles, physical constraints, process knowledge, and data-driven intelligence have contributed to more reliable operational decisions. The second objective has been to evaluate the influence of Digital Twin Integration Capability on the dependent performance construct, particularly through virtual representation, physical-digital synchronization, condition visualization, simulation, and decision support. The third objective has been to determine how Real-Time Industrial Data Intelligence has influenced predictive maintenance and energy optimization performance through continuous sensing, data acquisition, condition monitoring, process-data integration, and timely analytical interpretation. The fourth objective has been to investigate the contribution of Predictive Maintenance Intelligence Capability by examining fault identification, degradation monitoring, anomaly detection, maintenance prioritization, and equipment-health prediction. The fifth objective has been to assess the contribution of Energy Optimization Intelligence Capability through the monitoring and analytical management of energy consumption, hydrogen-related operating conditions, equipment efficiency, and process performance. A further objective has been to statistically validate the combined explanatory capacity of these five independent variables using correlation and multiple regression analysis. Through these objectives, the study has established a measurable framework in which physics-informed intelligence, virtual-system representation, real-time data, maintenance analytics, and energy optimization have been examined simultaneously rather than as isolated technological functions.

Research Hypotheses

The hypotheses of this study have been developed to test the proposed relationships between five independent technological capabilities and Predictive Maintenance and Energy Optimization Performance in hydrogen-integrated industrial systems. H1 has stated that Physics-Informed AI Capability has a significant positive effect on Predictive Maintenance and Energy Optimization Performance. This hypothesis has reflected the expectation that combining operational data with engineering principles, physical constraints, and process knowledge can strengthen the reliability of maintenance and energy-related analytical decisions. H2 has stated that Digital Twin Integration Capability has a significant positive effect on Predictive Maintenance and Energy Optimization Performance, based on the role of synchronized virtual representations in condition monitoring, simulation, degradation assessment, and operational decision support. H3 has stated that Real-Time Industrial Data Intelligence has a significant positive effect on Predictive Maintenance and Energy Optimization Performance, treating continuous sensing, timely data acquisition, process-state monitoring, and integrated analytical interpretation as essential components of real-time industrial decision-making. H4 has stated that Predictive Maintenance Intelligence Capability has a significant positive effect on Predictive Maintenance and Energy Optimization Performance by supporting stronger fault detection, anomaly identification, degradation assessment, equipment-health monitoring, and maintenance prioritization. H5 has stated that Energy Optimization Intelligence Capability has a significant positive effect on Predictive Maintenance and Energy Optimization Performance by supporting analytical control of energy consumption, equipment efficiency, hydrogen-process performance, and operating conditions. Collectively, these hypotheses have enabled the study to examine both individual predictor effects and the explanatory power of the complete regression model. Each hypothesis has been evaluated statistically using data collected through a structured five-point Likert-scale questionnaire, with Pearson correlation analysis used to establish the direction and strength of relationships and multiple linear regression used to determine the independent contribution and statistical significance of each technological capability.

Significance of the Research

i. Integrated technical significance: The study has brought physics-informed artificial intelligence, digital twins, real-time industrial data intelligence, predictive maintenance, and energy optimization into a single empirical framework. This integration has been important because these capabilities have frequently been investigated separately even though they function as connected components of advanced hydrogen-integrated industrial systems.

ii. Maintenance-management significance: The research has provided a structured basis for examining how advanced analytical capabilities support equipment-condition monitoring, anomaly identification, degradation assessment, fault prediction, and maintenance decision-making. It has also clarified the individual statistical contribution of specialized technological capabilities to predictive maintenance performance.

iii. Energy-management significance: The study has treated maintenance and energy optimization as related performance dimensions rather than independent operational concerns. This treatment has reflected the fact that equipment degradation, inefficient operating conditions, unstable processes, and inappropriate maintenance decisions can directly influence industrial energy consumption and hydrogen-system efficiency.

iv. Methodological significance: The research has operationalized five specialized technological capabilities as measurable constructs and has evaluated them through a quantitative, explanatory, cross-sectional, case-study-based design. Reliability analysis, validity assessment, descriptive statistics, Pearson correlation analysis, and multiple linear regression have provided a coherent statistical structure for evaluating the proposed relationships.

v. Industrial decision-support significance: The research has offered a framework relevant to industrial managers, maintenance professionals, energy specialists, digital-twin developers, automation personnel, and AI practitioners seeking to understand how physical knowledge, real-time data, virtual representation, maintenance intelligence, and optimization capability interact in hydrogen-related industrial environments.

vi. Theoretical significance: By relating the technological constructs to Cyber-Physical Systems

Theory, the study has provided an organized explanation of how physical industrial assets, sensing infrastructure, computational models, digital representations, analytical intelligence, and operational decisions are interconnected within a unified physical-digital system.

vii. Hydrogen-system significance: The research has focused specifically on hydrogen-integrated industrial environments rather than treating advanced industrial intelligence as a generic manufacturing concept. This specialization has enabled the study to address operational complexity associated with hydrogen production, storage, compression, distribution, conversion, equipment condition, and energy-intensive process integration.

LITERATURE REVIEW

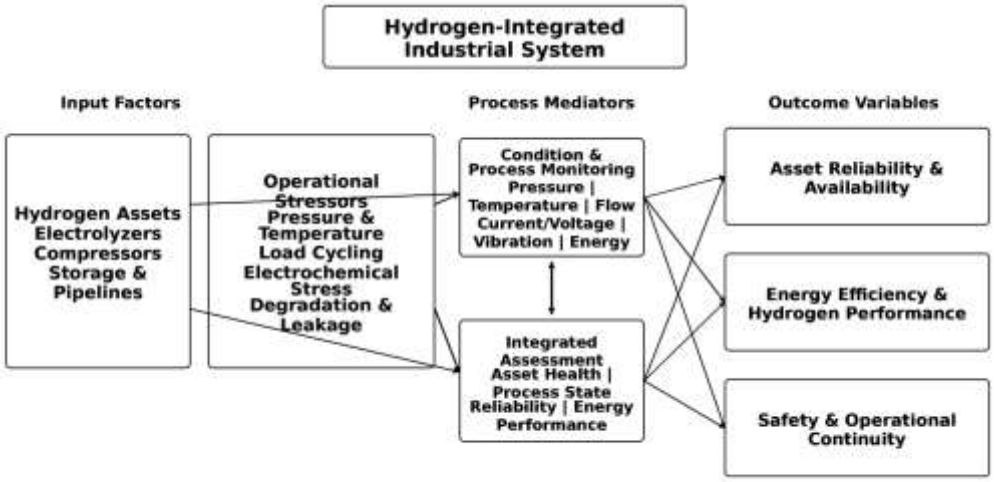
The literature concerning physics-informed artificial intelligence, digital twins, predictive maintenance, industrial data intelligence, hydrogen technologies, and energy optimization has represented several closely related but historically distinct research streams. Hydrogen-integrated industrial systems combine energy conversion, industrial processing, mechanical equipment, electrochemical technologies, storage infrastructure, digital monitoring systems, and automated control mechanisms, creating a technical environment in which equipment reliability and energy performance cannot be examined independently. Within this environment, physics-informed artificial intelligence has provided a mechanism for combining observed industrial data with governing equations, engineering constraints, physical principles, and process knowledge, allowing analytical models to represent both statistical relationships and physically meaningful system behavior. Digital twins have provided another essential component by maintaining virtual representations of physical assets, equipment, and processes that can be updated through real-time operational information and used for monitoring, simulation, diagnostics, prediction, and optimization. Real-time industrial data intelligence has connected the physical and virtual dimensions of the system by collecting, processing, integrating, and interpreting information from sensors, industrial Internet of Things devices, control platforms, supervisory systems, and equipment-monitoring technologies. Predictive maintenance has transformed these data and analytical capabilities into equipment-health intelligence by identifying abnormalities, evaluating degradation, anticipating failures, and supporting maintenance prioritization. Energy optimization has extended the analytical scope toward energy consumption, process efficiency, hydrogen-production performance, equipment loading, operational conditions, and resource utilization. These research areas have become particularly important when considered together because maintenance decisions can influence energy efficiency, while inefficient or abnormal energy behavior may also provide information about equipment deterioration. The literature review has therefore examined the technological, theoretical, and empirical relationships among Physics-Informed AI Capability, Digital Twin Integration Capability, Real-Time Industrial Data Intelligence, Predictive Maintenance Intelligence Capability, Energy Optimization Intelligence Capability, and Predictive Maintenance and Energy Optimization Performance, with particular attention to Cyber-Physical Systems Theory and the conceptual relationships tested in this study.

Hydrogen-Integrated Industrial Systems and Operational Challenges

Hydrogen-integrated industrial systems combine hydrogen production, conditioning, compression, storage, transport, distribution, and end-use technologies with conventional industrial equipment, digital control systems, and energy-management infrastructures. Their operational structure is therefore more complex than a single hydrogen-production unit because performance depends on coordinated behavior across electrolyzers, compressors, storage vessels, pipelines, valves, heat exchangers, sensors, control devices, and downstream process equipment. In "Hydrogen Storage and Delivery" (pp. 12254-12269), the technical chain from storage to delivery has been examined together with risk and reliability requirements, showing that hydrogen infrastructures must be understood as interconnected systems in which component condition, containment integrity, pressure management, and delivery reliability influence system-level operation (Ashik & Shabbir, 2022; Moradi & Groth, 2019). Storage options also differ substantially in pressure, temperature, material requirements, energy demand, and failure modes, while delivery arrangements introduce additional dependencies associated with compression, transport distance, transfer equipment, and operating environment. These characteristics make energy efficiency and asset reliability mutually dependent operational

concerns. In "Review of Transportation Hydrogen Infrastructure Performance and Reliability" (pp. 12010-12023), hydrogen infrastructure performance has been linked to availability, maintenance activity, throughput, and operating cost, emphasizing that reliability problems at component level can affect the economic and functional performance of the complete hydrogen supply system (Hasan & Adnan, 2022; Kurtz et al., 2019). For industrial facilities, the same systems logic applies when hydrogen is integrated into production plants, chemical processes, steelmaking, refining, power systems, or other energy-intensive operations. A compressor fault, storage limitation, electrolyzer efficiency loss, sensor deviation, or control-system disturbance can influence hydrogen availability, process continuity, energy consumption, and maintenance requirements simultaneously. Consequently, hydrogen integration creates an operational environment in which physical asset health, process variables, energy flows, and maintenance decisions must be evaluated as connected dimensions of system performance rather than as isolated engineering problems. This interdependence places monitoring, reliability assessment, maintenance coordination, and energy management at the center of hydrogen-integrated industrial performance.

Figure 2: Hydrogen-Integrated Industrial Operational Challenges and Performance Pathways



The physical properties of hydrogen create additional operational challenges because materials and components can respond differently under hydrogen exposure than under conventional service environments. High-pressure operation, cyclic loading, temperature variation, repeated start-stop conditions, permeation, leakage, and contact with susceptible metallic materials can progressively alter the reliability of hydrogen-related equipment. In "Hydrogen Related Degradation in Pipeline Steel" (pp. 14584-14617), hydrogen-induced cracking, stress-oriented hydrogen-induced cracking, sulfide stress corrosion cracking, microstructural sensitivity, and the interaction of hydrogen concentration with tensile stress have been examined as important mechanisms affecting pipeline integrity (Mahbubul et al., 2022; Ohaeri et al., 2018). These mechanisms are important for industrial maintenance because deterioration may develop internally before obvious external symptoms become available to operators. Similar degradation concerns occur within hydrogen-production equipment. In "Impact of Intermittent Operation on Photovoltaic-PEM Electrolyzer Systems" (pp. 683-695), accelerated stress testing has shown that dynamic operating profiles and shutdown periods can influence degradation behavior in proton exchange membrane water electrolyzers, demonstrating that operating pattern itself can become a determinant of component aging and performance loss (Kuhnert et al., 2024; Mashfiqur & Md, 2022). Hydrogen-integrated industrial systems may therefore experience degradation that is driven not only by accumulated operating hours but also by load transitions, thermal conditions, electrochemical stress, pressure variation, and interaction among subsystems. These characteristics reduce the adequacy of maintenance strategies based only on fixed intervals because equivalent operating time does not necessarily indicate equivalent equipment condition. Real-time monitoring becomes important for distinguishing normal process variability from emerging deterioration.

Variables such as pressure, temperature, current density, voltage, vibration, flow rate, hydrogen purity, energy consumption, and equipment-state indicators can collectively provide evidence about asset health. However, interpreting these signals requires an analytical framework capable of connecting observed changes to known physical behavior, degradation mechanisms, and operating constraints. Effective maintenance assessment must therefore account for both immediate equipment condition and the physical operating history that produced that condition.

Safety and operational continuity form another critical dimension of hydrogen-integrated industrial systems because abnormal events can develop rapidly when leakage, ignition, confinement, pressure, and combustible mixtures interact. In "Review on Hydrogen Safety Issues" (pp. 31467-31488), incident statistics, hydrogen leakage and diffusion, ignition behavior, and explosion processes have been synthesized to show that safe hydrogen operation depends on understanding both initiating failures and the physical development of hazardous events (Ashfaq & Mohammad, 2022; Yang et al., 2021). For industrial environments, this means that maintenance intelligence cannot be separated from process-state awareness. A deteriorating seal, valve, pipe section, sensor, compressor, or storage component may initially appear as a localized equipment problem but can also alter pressure stability, hydrogen concentration, system availability, energy efficiency, or safety margins. The operational challenge is intensified by the large volume and speed of data generated by modern industrial sensing and control systems. Conventional alarms can identify threshold violations, but they may provide limited information about the degradation process that produced the abnormal state or the remaining time before functional performance is affected. Hydrogen-integrated operations therefore require a more integrated representation of equipment condition, process physics, historical behavior, and current sensor information. Predictive maintenance can provide estimates of fault development and equipment condition, while energy optimization can evaluate how operating choices affect energy use, hydrogen output, and system efficiency. Yet the two functions are technically connected because degraded assets can consume more energy, unstable operation can accelerate wear, and energy-minimizing operating points may be inappropriate when equipment condition is ignored. The specific operational context of hydrogen systems therefore provides a strong basis for combining real-time data intelligence with digital representation and physics-based analytical knowledge. This combination allows maintenance and energy performance to be examined within the same system boundary, which is essential for the quantitative framework adopted in this study.

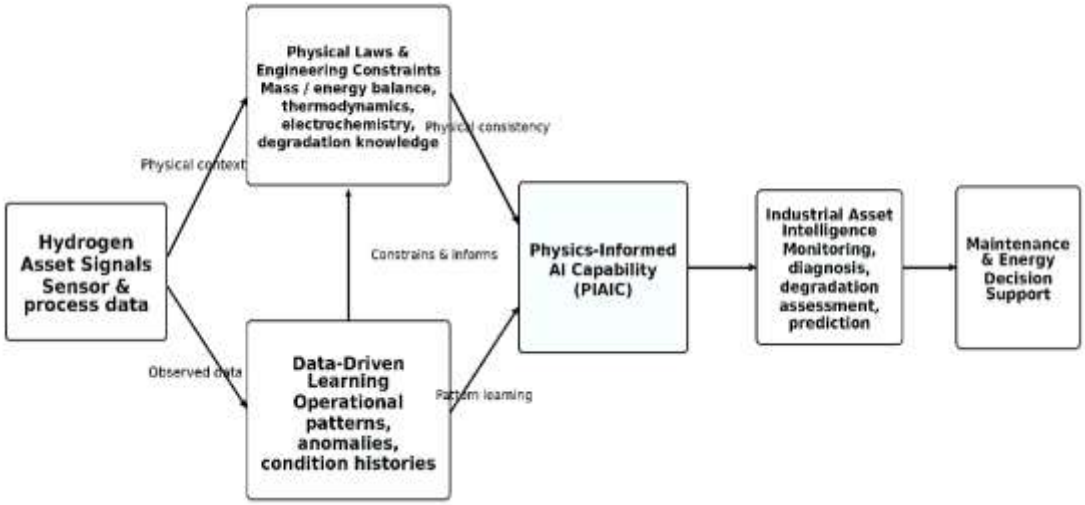
Physics-Informed Artificial Intelligence for Industrial Asset Intelligence

Physics-informed artificial intelligence represents an approach to industrial intelligence in which machine-learning models are developed together with scientific knowledge, governing equations, physical constraints, and engineering rules so that predictions remain connected to the behavior of the real system. For hydrogen-integrated industrial assets, this approach is especially relevant because equipment condition is shaped by thermodynamic, electrochemical, mechanical, fluid-dynamic, and material processes that cannot always be represented adequately through historical data alone. In "Theory-Guided Data Science" (pp. 2318-2331), scientific theories and domain knowledge have been positioned as explicit resources that can constrain, regularize, or structure data-driven models when purely statistical learning produces physically inconsistent relationships or requires unrealistically large datasets (Karpatne et al., 2017; Sadia & Mostari, 2022). This principle is directly applicable to hydrogen compressors, electrolyzers, pumps, pipelines, storage units, valves, heat exchangers, and power-electronic subsystems because measurable signals such as pressure, temperature, voltage, current, vibration, flow, and energy consumption are generated by underlying physical mechanisms. Physics-informed AI can therefore combine these observations with mass balance, energy balance, degradation laws, electrochemical relationships, pressure-flow behavior, heat-transfer equations, and operating limits. In "Integrating Scientific Knowledge with Machine Learning for Engineering and Environmental Systems" (pp. 1-37), several knowledge-integration strategies have been organized around the use of scientific knowledge in model inputs, architectures, objective functions, hybrid models, and model outputs, demonstrating that physics can enter the learning process at multiple stages rather than through a single standardized mechanism (Shaiful et al., 2022; Willard et al., 2022). For industrial asset intelligence, this flexibility is important because the available physical knowledge differs across components. A compressor may be represented through rotational dynamics and

thermodynamic relations, while an electrolyzer may require electrochemical and thermal constraints. Physics-Informed AI Capability therefore represents the organizational and technical capacity to reliably embed appropriate physical knowledge into data-driven monitoring, diagnosis, prediction, and optimization rather than treating AI as an independent black-box analytical layer.

Physics-informed AI becomes especially important in condition monitoring and fault diagnosis, where industrial datasets often contain few failure examples, changing operating regimes, sensor noise, and substantial normal process variability. Conventional deep-learning models can classify patterns effectively when representative labeled data are abundant, but industrial systems rarely generate balanced datasets containing every possible failure condition. Failure data are sparse, costly, and strongly condition dependent. In "Physics-Based Convolutional Neural Network for Fault Diagnosis of Rolling Element Bearings" (pp. 4181-4192), physical knowledge of bearing fault characteristics has been incorporated into a convolutional neural-network framework to address limitations associated with exclusively data-driven diagnosis, illustrating how engineering knowledge can guide feature learning and improve fault interpretation across machinery components (Sadoughi & Hu, 2019; Stabak & Md Shahid, 2022).

Figure 3: Physics-Informed AI Pathway for Industrial Asset Intelligence



This type of integration is relevant to hydrogen-integrated facilities because rotating machinery such as compressors, pumps, motors, and auxiliary equipment can produce vibration signatures whose meaning depends on operating speed, loading, structural characteristics, and fault mechanics. Physics-informed models can distinguish patterns that are statistically unusual from those that are mechanically or thermodynamically inconsistent with expected system behavior. In "Physics-Informed Machine Learning in Prognostics and Health Management" (pp. 325-352), physics-informed prognostics and health management has been organized according to forms of informed knowledge and methods of incorporating that knowledge into learning, with particular attention to diagnosis, degradation assessment, and remaining-useful-life prediction (Abdullah Mohammad, 2023; Deng et al., 2023). For the present research, this literature supports treating physics-informed AI as more than an algorithmic technique. It constitutes a system-level capability through which engineering knowledge and operational data are jointly used to estimate asset condition, detect anomalies, represent degradation, and support maintenance decisions. Such capability can be particularly important operationally when hydrogen-related components operate under dynamic loading, repeated cycling, high pressure, thermal variation, or other conditions in which the same sensor value may have different meanings under different physical states.

Physics-informed AI strengthens industrial asset intelligence by connecting condition monitoring with reliability and system-safety analysis. A maintenance system must identify abnormal observations while assessing whether predicted states are credible, physically feasible, and relevant to equipment

reliability. In "Physics-Informed Machine Learning: A Comprehensive Review on Applications in Anomaly Detection and Condition Monitoring" (Article 124678), physics-informed methods have been shown to combine domain knowledge with machine learning for anomaly detection and engineering-system monitoring, particularly where purely physical models are incomplete and purely data-driven approaches face interpretability or data limitations (Adnan & Iftekhar, 2023; Wu et al., 2024). This perspective is relevant to hydrogen-integrated industrial systems because the consequences of inaccurate state estimation can extend from inefficient maintenance scheduling to loss of availability, abnormal process operation, or weakened safety margins. Physics-based constraints can reduce the solution space available to an AI model and can therefore prevent some predictions that fit observed data statistically but violate known system behavior. The analytical value of such constraints also extends to uncertainty management, because physics can help determine whether a prediction falls within a realistic operating envelope even when historical examples are limited.

Condition-monitoring applications provide a basis for evaluating this capability empirically. Within the present study, Physics-Informed AI Capability consequently includes the ability to use physical laws, engineering constraints, domain models, degradation knowledge, and real-time operational data within AI-supported analysis. Its expected contribution to predictive maintenance and energy optimization performance arises from the integration of data interpretation with physically meaningful system representation. For hydrogen-integrated assets, such integration allows maintenance intelligence to consider whether emerging changes in pressure, temperature, vibration, flow, electrical demand, hydrogen production, or efficiency are consistent with normal operating transitions or indicate physically plausible deterioration that requires intervention. It also allows energy-oriented decisions to remain consistent with process limits and asset-health requirements, making physics-informed AI a central analytical component of the proposed cyber-physical framework.

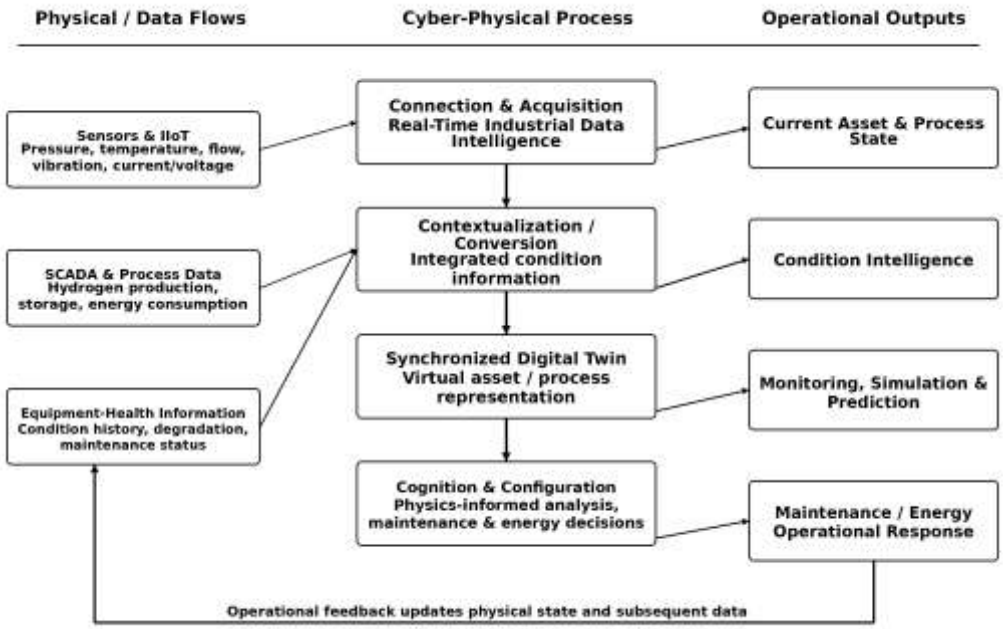
Digital Twin Integration and Cyber-Physical Monitoring

Digital twin integration in advanced industrial environments is founded on continuous interaction between physical equipment, sensing infrastructure, computational representations, communication networks, and analytical systems. In hydrogen-integrated industrial systems, this interaction is particularly important because electrolyzers, compressors, pumps, storage vessels, pipelines, valves, power-electronic devices, and auxiliary machinery continuously generate operational information describing pressure, temperature, vibration, voltage, current, flow, hydrogen production, energy consumption, and equipment condition. A cyber-physical architecture provides the technological foundation through which these physical observations can be transferred into computational environments for interpretation and decision support. In "A Cyber-Physical Systems Architecture for Industry 4.0-Based Manufacturing Systems" (pp. 18-23), a five-level cyber-physical architecture consisting of connection, conversion, cyber, cognition, and configuration functions has been developed to explain how raw machine information can progress toward intelligent system-level decision-making and feedback, establishing an important structural basis for real-time industrial monitoring (Lee et al., 2015; Md Anisur Rahman, 2023). Within a hydrogen-integrated setting, the connection level can represent sensor acquisition from hydrogen-related assets, while conversion processes transform raw signals into condition-related information. Digital representations can then aggregate equipment information at the cyber level, analytical intelligence can support cognition, and maintenance or operational responses can represent configuration activities. In "The Digital Twin: Realizing the Cyber-Physical Production System for Industry 4.0" (pp. 335-340), automated acquisition of production information and the creation of sufficiently synchronized digital representations have been presented as essential elements for linking real production environments with their virtual counterparts and reducing dependence on manually collected process information (Md Asif Ali Sheak & Tahmedur, 2023; Uhlemann et al., 2017). Such integration is highly relevant to hydrogen systems because equipment conditions can change rapidly under varying loads, pressures, temperatures, and production demands. Digital Twin Integration Capability therefore requires more than a static simulation model. It requires an operational connection through which the virtual representation remains sufficiently synchronized with the physical hydrogen system to support monitoring, diagnosis, predictive analysis, and informed responses to changing asset and process conditions.

Real-Time Industrial Data Intelligence represents the capability to collect, communicate, organize,

contextualize, and analyze continuously generated industrial information so that changing equipment and process states can be interpreted with minimal delay. The emergence of Industrial Internet of Things technologies has strengthened this capability by extending connectivity beyond conventional isolated automation systems and enabling interaction among sensors, controllers, computing platforms, machines, and enterprise-level information systems. In "The Industrial Internet of Things (IIoT): An Analysis Framework" (pp. 1-12), industrial connectivity has been examined through the relationship among IIoT devices, industrial automation and control systems, cyber-physical systems, and Industry 4.0 architectures, showing that connected industrial environments involve heterogeneous devices with distinct functions, physical locations, communication characteristics, and security requirements (Boyes et al., 2018; Md Kaium, 2023).

Figure 4: Digital Twin and Real-Time Data Cyber-Physical Monitoring Framework



This heterogeneous structure closely corresponds to hydrogen-integrated plants, where process-control information, equipment-health measurements, energy data, environmental measurements, and safety-related signals may originate from different systems but must collectively represent the actual operating state. Real-time data intelligence therefore involves more than increasing sensor quantity. Data must be temporally aligned, technically meaningful, sufficiently accurate, accessible to analytical models, and associated with the specific physical asset or process represented by the digital twin. In "Digital Twin: Values, Challenges and Enablers From a Modeling Perspective" (pp. 21980-22012), digital twins have been described through the interaction of data, simulation, computational models, and physical assets for real-time monitoring, prediction, optimization, control, and decision-making, while enabling technologies include sensing, artificial intelligence, computational infrastructure, and data-management capabilities (Md Mahamud Pervaz, 2023; Rasheed et al., 2020). For hydrogen-integrated systems, this relationship means that a digital representation becomes operationally useful when continuously updated information can identify the current condition of relevant equipment and processes. Pressure variation, abnormal vibration, declining electrolyzer efficiency, changing electrical demand, unexpected temperature behavior, and deviations in hydrogen flow can then be interpreted within a synchronized representation rather than as disconnected signals.

The integration of digital twins and real-time data intelligence also creates a system-level monitoring environment in which physical observations can be interpreted together with simulation results, historical behavior, maintenance information, and analytical predictions. This capability is central to the present study because predictive maintenance requires reliable knowledge of equipment condition, while energy optimization requires timely information about operating efficiency and energy-related

process behavior. In hydrogen-integrated industrial systems, these objectives are interconnected because deterioration in compressors, electrolyzers, pumps, thermal-management systems, or other supporting assets may simultaneously change reliability indicators and energy-performance characteristics. A digital twin can organize these relationships by associating physical components with corresponding virtual states and continuously incorporating operational data into the representation. In "Digital Twin Paradigm: A Systematic Literature Review" (Article 103469), digital twins have been characterized as synchronized virtual representations whose architectures combine physical entities, digital components, data, communication mechanisms, models, and services across different application domains, while synchronization and information exchange remain fundamental to maintaining meaningful correspondence between physical and virtual systems (Mohammad Badrul & Md. Mominul, 2023; Semeraro et al., 2021). For the present research, Digital Twin Integration Capability therefore refers to the extent to which industrial organizations can establish and maintain dynamic virtual representations of hydrogen-related assets and processes, whereas Real-Time Industrial Data Intelligence represents their capability to transform continuously generated operational information into timely and usable knowledge. The two constructs are analytically distinct because an organization may possess extensive sensing and data infrastructure without an integrated digital twin, while a digital model may exist without sufficiently continuous or high-quality real-time synchronization. Their combination enables cyber-physical monitoring in which equipment state, process behavior, maintenance condition, and energy performance can be examined within a common information environment. This provides the technical basis for evaluating whether stronger digital-twin integration and real-time industrial data intelligence are associated with higher Predictive Maintenance and Energy Optimization Performance in hydrogen-integrated industrial systems.

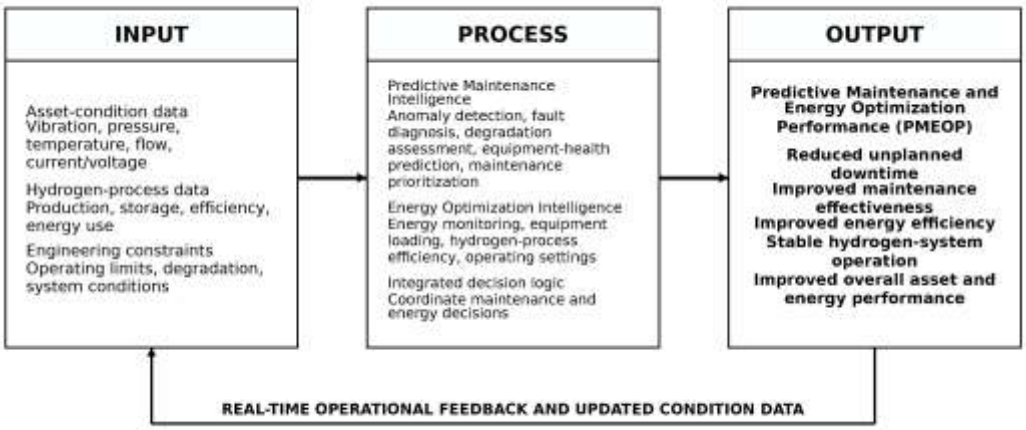
Energy Optimization in Hydrogen-Integrated Industrial Systems

Predictive maintenance in hydrogen-integrated industrial systems requires continuous assessment of equipment condition because failures in electrochemical devices, compression units, pumps, storage components, and auxiliary systems can interrupt hydrogen availability and alter energy performance. In "A Review on Prognostics and Health Monitoring of Proton Exchange Membrane Fuel Cell" (pp. 440-450), prognostics and health monitoring have been presented as mechanisms for estimating state of health, remaining useful life, reliability, and maintenance needs in proton exchange membrane fuel cells, highlighting their role in reducing unscheduled maintenance and operational disruption (Molla Al Rakib & Mohammad Towhidul, 2023; Sutharssan et al., 2017). This perspective is directly relevant to hydrogen-integrated industrial systems because fuel cells and related electrochemical assets experience gradual degradation that may not be captured adequately by fixed maintenance intervals. Predictive maintenance therefore depends on transforming monitored variables into indicators that describe emerging deterioration before functional failure occurs. In "A Non-Intrusive Signal-Based Fault Diagnosis Method for Proton Exchange Membrane Water Electrolyzer Using Empirical Mode Decomposition" (Article 4458), variations in electrolyzer current have been decomposed into intrinsic mode functions so that the energetic contribution of signal components can be used to identify anode pump and flow-related faults while allowing the electrolyzer to remain operational during diagnosis (Aubras et al., 2021; Mukut Kanti, 2023). Such approaches demonstrate the value of non-intrusive monitoring for hydrogen-production assets where stopping equipment for frequent inspection can reduce availability and production efficiency. Within an integrated plant, predictive maintenance must therefore combine electrical, mechanical, thermal, electrochemical, and process information. Voltage decline may indicate electrochemical aging, abnormal current behavior may reflect flow or pump problems, vibration may indicate rotating-equipment deterioration, and pressure or temperature deviations may reveal developing process faults. The maintenance challenge is to distinguish normal operational variability from fault-related behavior while preserving sufficient sensitivity for early intervention, making condition intelligence a central capability of hydrogen-system management and real-time industrial maintenance decision support.

The predictive-maintenance problem becomes more demanding when industrial hydrogen equipment operates under dynamic conditions in which process variables are serially correlated, measurements contain uncertainty, and several faults produce overlapping signatures. In "Dynamic Fault Detection and Diagnosis of Industrial Alkaline Water Electrolyzer Process With Variational Bayesian Dictionary

Learning" (pp. 1492-1506), an industrial alkaline water electrolysis process has been examined through a robust dynamic variational Bayesian dictionary-learning method designed to preserve process structure, extract autocorrelation, and identify critical fault variables under measurement uncertainty (Nishat, 2023; Zhang et al., 2024). The study is relevant to hydrogen-integrated industrial systems because alkaline electrolysis produces interacting process variables whose current values depend partly on previous operating states. This temporal dependency complicates threshold-based monitoring, since an isolated deviation may reflect an intentional load transition rather than equipment deterioration. Predictive maintenance therefore requires methods that evaluate relationships among variables, operating history, and process dynamics rather than assessing measurements independently. The same principle applies beyond electrolyzers.

Figure 5: Integrated Predictive Maintenance and Energy Optimization Process



Hydrogen compressors can experience valve, piston, seal, lubrication, and vibration-related deterioration; storage systems can develop pressure-management or containment problems; pumps and thermal-management equipment can show gradual efficiency losses; and sensors can generate drifting or uncertain measurements. A meaningful maintenance architecture must integrate these signals into a consistent representation of equipment health. It must also support early fault detection without excessive false alarms that could trigger unnecessary maintenance interventions. In the present research, Predictive Maintenance Intelligence Capability represents more than the existence of sensors or maintenance software. It reflects the ability of an industrial system to transform real-time operational data into reliable anomaly detection, fault diagnosis, degradation assessment, equipment-health evaluation, and maintenance prioritization. This capability is significant when maintenance decisions must be coordinated with hydrogen-production requirements and energy-management objectives, because taking equipment offline, reducing loads, or changing operating conditions can affect overall production continuity and energy performance.

Energy optimization is closely connected with predictive maintenance because the operating condition of hydrogen equipment affects energy consumption and the rate at which components experience stress and degradation. In "Optimal Energy Management of Hydrogen Energy Facility Using Integrated Battery Energy Storage and Solar Photovoltaic Systems" (pp. 1457-1468), an energy-management model has been formulated to minimize the net cost of an industrial hydrogen facility while coordinating electrolyzer operation, photovoltaic generation, battery storage, hydrogen storage, electricity prices, and reliable system operation (Abomazid et al., 2022; Risha & Mst Shurovi, 2023). The study illustrates that hydrogen-energy performance depends on coordinated scheduling rather than maximizing a single component's efficiency. Operating decisions determine when hydrogen is produced, how stored energy is used, and how electrical demand interacts with hydrogen demand. In "Multi-Objective Optimization of CO2 Emission and Thermal Efficiency for On-Site Steam Methane Reforming Hydrogen Production Process Using Machine Learning" (Article 132133), a hybrid deep neural-network model and multi-objective particle-swarm optimization have been used to identify

operating solutions that jointly consider thermal efficiency and carbon emissions in hydrogen production (Hong et al., 2022; Stabak & Md Siam, 2023). This demonstrates that optimization in hydrogen systems involves competing performance objectives and constraints. For industrial predictive maintenance, the relationship is important because an energy-efficient operating point may impose thermal, mechanical, or electrochemical stress that accelerates equipment degradation, while degraded equipment can increase energy demand and reduce hydrogen-production efficiency. An integrated decision structure must therefore evaluate energy use together with asset condition, production requirements, system constraints, and maintenance status. Energy Optimization Intelligence Capability in this study refers to the ability to use operational data and analytical models to improve energy allocation, equipment loading, hydrogen-production efficiency, storage utilization, and process settings while maintaining operation. Predictive Maintenance and Energy Optimization Performance captures a combined outcome in which equipment health, downtime, reliability, energy consumption, and hydrogen-system performance are assessed within the industrial framework.

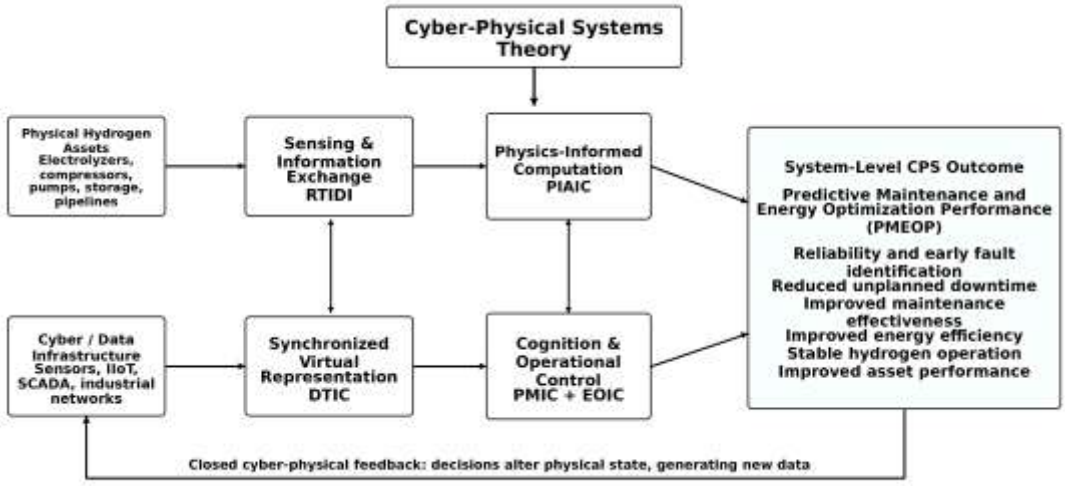
Cyber-Physical Systems Theory as the Theoretical Framework

Cyber-Physical Systems Theory provides the most appropriate theoretical foundation for this study because it explains how physical industrial processes, sensing infrastructure, computational intelligence, communication networks, and control decisions operate as a continuously connected system. In "Design Techniques and Applications of Cyberphysical Systems" (pp. 350-365), cyber-physical systems have been described as engineered systems in which computational and physical components are deeply integrated and interact through sensing, communication, processing, and control, making the theory suitable for environments where real assets and digital intelligence must function together (Khaitan & McCalley, 2015; Syed Feroz, 2023). Hydrogen-integrated industrial systems possess this exact structure because electrolyzers, compressors, pumps, storage vessels, pipelines, thermal equipment, power-electronic devices, and auxiliary machinery constitute the physical layer, while sensors, industrial networks, analytics platforms, digital twins, and AI models constitute the cyber layer. In "Cyber-Physical Systems Challenges" (pp. 5-16), the interaction between embedded computation and physical processes has been treated as a central design requirement, with attention given to coordination across software, hardware, communication, and physical behavior (Mosterman & Zander, 2016; Tahmedur & Rifat, 2023). For the present research, this theoretical logic means that physical hydrogen-system behavior cannot be analyzed independently from the digital mechanisms used to observe, interpret, predict, and influence that behavior. Physics-Informed AI Capability represents computational intelligence that embeds physical laws and engineering constraints into analytical processes; Digital Twin Integration Capability represents the virtualized and synchronized representation of the physical system; Real-Time Industrial Data Intelligence represents the sensing and information-exchange mechanism connecting physical assets with digital models; Predictive Maintenance Intelligence Capability represents diagnostic and prognostic reasoning; and Energy Optimization Intelligence Capability represents analytical control of energy-related decisions. Predictive Maintenance and Energy Optimization Performance becomes the system-level outcome produced when these cyber and physical capabilities operate coherently. The theory therefore provides a direct explanation for why the five independent constructs should be examined jointly rather than as unrelated technologies.

The theoretical relevance becomes stronger when cyber-physical integration is considered as a closed interaction rather than a one-directional flow of information. In "Design, Modelling, Simulation and Integration of Cyber Physical Systems" (pp. 273-289), cyber-physical system development has been presented as a multidisciplinary process in which physical processes, computation, modeling, simulation, and system integration must be designed together, including condition-monitoring functions that support maintenance assessment (Asheke, 2024; Hehenberger et al., 2016). In a hydrogen-integrated industrial environment, the physical system generates real-time signals such as pressure, temperature, flow, current, voltage, vibration, hydrogen output, and energy consumption. These signals are contextualized through Real-Time Industrial Data Intelligence, transferred into a synchronized Digital Twin, interpreted through Physics-Informed AI, and transformed into maintenance or energy-related decisions. The intervention changes the physical operating state, after which new sensor information enters the cyber layer and the cycle repeats. In "A Review on the

Characteristics of Cyber-Physical Systems for the Future Smart Factories" (pp. 305-335), cyber-physical systems have been characterized through technological and operations-management features including connectivity, communication, real-time capability, computational capability, adaptability, predictability, diagnosability, and dynamic reconfiguration, which collectively explain responsive industrial operation (Ashrafuzzaman, 2024; Napoleone et al., 2020). This feedback logic provides the theoretical basis for expecting stronger digital integration and analytical intelligence to correspond with stronger system performance. It also clarifies that the five predictors are complementary but analytically separable capabilities.

Figure 6: Cyber-Physical Systems Theoretical Framework for Hydrogen-Integrated Industrial Intelligence



A plant may possess extensive sensor infrastructure while lacking a synchronized twin, or it may employ a digital model without physics-informed analytical intelligence. Similarly, predictive maintenance can exist without coordinated energy optimization. Cyber-Physical Systems Theory allows these capabilities to be represented as distinct dimensions of one integrated industrial architecture. The theory supports the study's explanatory, cross-sectional design because respondent assessments can measure the maturity of each cyber-physical capability and determine whether higher capability levels are statistically associated with improved predictive maintenance and energy optimization outcomes.

$$PMEOP_i = \beta_0 + \beta_1 PIAIC_i + \beta_2 DTIC_i + \beta_3 RTIDI_i + \beta_4 PMIC_i + \beta_5 EOIC_i + \varepsilon_i$$

To operationalize this theoretical logic quantitatively, the study has used a multiple linear regression model as the principal equation linking cyber-physical capabilities to the common performance outcome. In "A Review of the Roles of Digital Twin in CPS-Based Production Systems" (pp. 939-948), digital twins have been positioned within cyber-physical production systems as virtual representations that support monitoring, synchronization, prediction, and control across the lifecycle of physical assets, reinforcing the role of the twin as a connective element between physical and computational domains (Mashiat, 2024; Negri et al., 2017). The empirical model adopted for the present study has specified Predictive Maintenance and Energy Optimization Performance as the dependent variable and the five cyber-physical capabilities as simultaneous predictors. In this specification, the intercept represents the expected value of the outcome when predictor scores are zero, the beta coefficients represent the unique statistical contribution of each technological capability when the other predictors are held constant, and the error term represents unexplained variation. This equation has been selected because it corresponds directly to H1 through H5 and allows the individual contribution of each capability to be evaluated without treating the constructs as a simple sequential causal chain. Pearson correlation analysis has first established the direction and strength of bivariate associations, after which the regression coefficients, R^2, adjusted R^2, F statistic, t statistics, and p values have determined the explanatory performance of the integrated model. The theoretical structure has therefore been translated into a

testable quantitative framework while preserving the study's cross-sectional design. It has also kept the theoretical framework aligned with the questionnaire structure, hypothesis set, conceptual model, statistical analysis, and interpretation of the empirical findings. Cyber-Physical Systems Theory has consequently functioned as the organizing logic connecting physical assets, sensing, digital twins, physics-informed intelligence, predictive maintenance, energy optimization, and system-level performance throughout the study.

Conceptual Framework and Hypothesized Relationships

The conceptual framework of this study integrates five technological capabilities within a single cyber-physical performance model for hydrogen-integrated industrial systems. Physics-Informed AI Capability represents the extent to which physical laws, engineering constraints, degradation knowledge, and process equations are incorporated into artificial-intelligence-supported monitoring and decision processes. Digital Twin Integration Capability represents the ability to create, synchronize, and use virtual representations of physical assets and processes. Real-Time Industrial Data Intelligence represents the continuous acquisition, integration, contextualization, and interpretation of sensor and operational information. Predictive Maintenance Intelligence Capability captures anomaly detection, fault diagnosis, degradation assessment, remaining-useful-life estimation, and maintenance prioritization, while Energy Optimization Intelligence Capability represents analytical control of energy use, operating conditions, hydrogen production, equipment loading, and process efficiency. In "Digital Twin-Driven Product Design, Manufacturing and Service with Big Data" (pp. 3563-3576), physical data, virtual-model data, and connected lifecycle information have been integrated within a digital-twin-driven manufacturing structure, supporting the conceptual treatment of digital representation and operational data as related but distinguishable capabilities (Md Kaium, 2024; Tao et al., 2018). In "Smart Manufacturing Systems for Industry 4.0" (pp. 137-150), smart monitoring, smart control, cyber-physical integration, Internet of Things connectivity, and big-data analytics have been organized within a unified manufacturing framework, supporting the inclusion of real-time data intelligence as an enabling construct rather than merely a measurement technology (Mukut Kanti, 2024; Zheng et al., 2018). Accordingly, the dependent construct, Predictive Maintenance and Energy Optimization Performance, represents the combined operational outcome of reliability, early fault identification, reduced unplanned downtime, improved maintenance effectiveness, improved energy efficiency, stable hydrogen-related operation, and better overall asset performance. The conceptual framework therefore proposes that each capability contributes independently to this common outcome while remaining part of the same integrated industrial architecture. This arrangement is especially appropriate for hydrogen facilities because operational decisions arise from interactions among physical assets, digital representations, analytical models, maintenance information, and energy-management requirements.

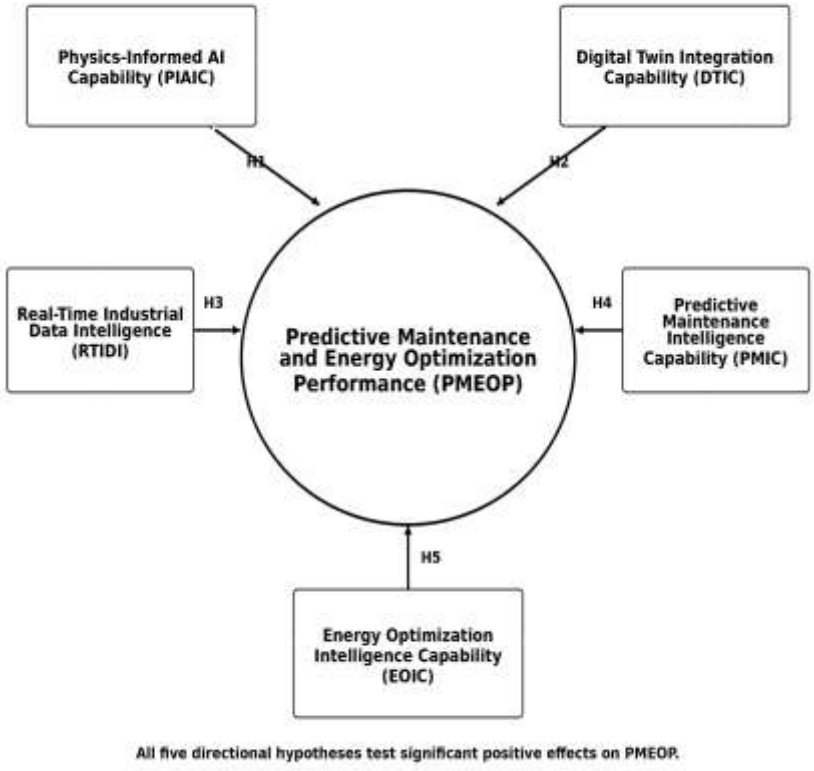
$$PMEOP = f(PIAIC, DTIC, RTIDI, PMIC, EOIC)$$

The hypothesized relationships follow directly from this conceptual structure. H1 proposes that stronger Physics-Informed AI Capability is positively associated with Predictive Maintenance and Energy Optimization Performance because physically constrained learning can improve the credibility of condition assessment, degradation modeling, and prediction when operating data are incomplete, noisy, or collected across changing regimes. In "Toward Physics-Informed Machine-Learning-Based Predictive Maintenance for Power Converters" (pp. 2692-2720), physics-informed methods have been reviewed across parameter identification, condition monitoring, fault diagnosis, and remaining-useful-life estimation, showing how prior physical knowledge can reduce dependence on large labeled datasets while improving interpretability and reliability in predictive-maintenance applications (Fassi et al., 2024; Syed Feroz, 2024). H2 proposes a positive relationship between Digital Twin Integration Capability and the dependent performance construct because synchronized virtual representations can consolidate asset states, simulations, degradation information, and maintenance knowledge around the physical system. H3 proposes that Real-Time Industrial Data Intelligence positively influences performance because predictive maintenance and energy optimization depend on timely and contextualized information describing equipment condition and process behavior. In "The Use of Digital Twin for Predictive Maintenance in Manufacturing" (pp. 1067-1080), digital-twin

representations have been connected with sensor measurements and physics-based models to support condition estimation and predictive-maintenance decisions, illustrating how physical-virtual integration can strengthen the translation of operational data into maintenance knowledge (Aivaliotis et al., 2019; Uddin & Risha, 2024). These relationships have been conceptually represented as a multivariate performance function in which the five capabilities are treated as simultaneous explanatory variables. The framework has not assumed that the predictors operate as a fixed sequence. Instead, each has been modeled as a distinct capability with a direct relationship to the common outcome, which is appropriate for the cross-sectional survey design and multiple-regression analysis used in this research.

$$PMEOP_i = \beta_0 + \beta_1 PIAIC_i + \beta_2 DTIC_i + \beta_3 RTIDI_i + \beta_4 PMIC_i + \beta_5 EOIC_i + \varepsilon_i$$

Figure 7: Conceptual Framework and Hypothesized Relationships



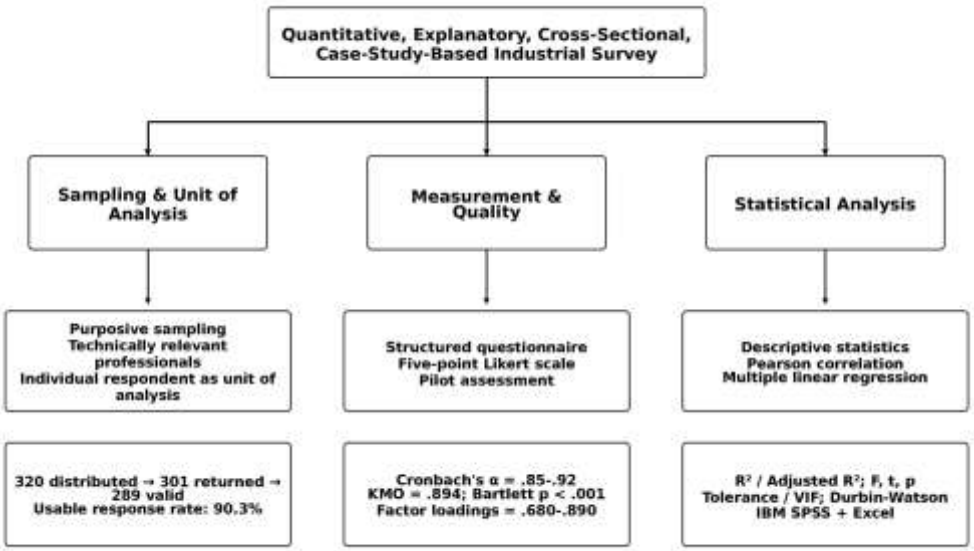
H4 proposes that Predictive Maintenance Intelligence Capability has a significant positive relationship with Predictive Maintenance and Energy Optimization Performance because stronger diagnostic, prognostic, and maintenance-prioritization capabilities should improve equipment availability, reduce avoidable interruption, and support condition-responsive operation. H5 proposes that Energy Optimization Intelligence Capability has a significant positive relationship with the same dependent performance construct because effective real-time energy monitoring and analytical optimization can improve resource allocation, equipment loading, hydrogen-production efficiency, and energy-related process performance. In "Energy Digital Twins in Smart Manufacturing Systems: A Literature Review" (pp. 1318-1325), energy-focused digital twins have been examined in relation to energy monitoring, consumption analysis, and optimization, demonstrating the relevance of synchronized operational data and virtual models for improving energy-oriented manufacturing decisions (Billey & Wuest, 2023; Jahanara, 2025). The complete conceptual model has therefore retained the same regression specification introduced by the theoretical framework. The directional hypothesis structure requires

positive beta coefficients for PIAIC, DTIC, RTIDI, PMIC, and EOIC, subject to statistical significance testing. This formulation has preserved consistency between the conceptual framework, H1 through H5, the five-point Likert measurement model, Pearson correlation analysis, and multiple linear regression, allowing the empirical study to determine both bivariate relationships and the unique contribution of each capability to integrated hydrogen-system maintenance and energy performance. It has also enabled examination of whether one capability adds explanatory value after controlling for the remaining capabilities. This matters because technological capabilities can coexist at different levels within the same industrial organization. A statistically significant positive coefficient has therefore been used to support the corresponding directional hypothesis, whereas a nonsignificant coefficient would have indicated that the proposed independent relationship was not supported by the sampled data.

METHOD

This study has adopted a quantitative, explanatory, cross-sectional, case-study-based industrial survey design to examine the relationships among Physics-Informed AI Capability (PIAIC), Digital Twin Integration Capability (DTIC), Real-Time Industrial Data Intelligence (RTIDI), Predictive Maintenance Intelligence Capability (PMIC), Energy Optimization Intelligence Capability (EOIC), and Predictive Maintenance and Energy Optimization Performance (PMEOP). A deductive analytical approach has been applied because theoretically specified relationships and predefined hypotheses have been tested using numerical data.

Figure 8: Quantitative Research Design and Analytical Procedure



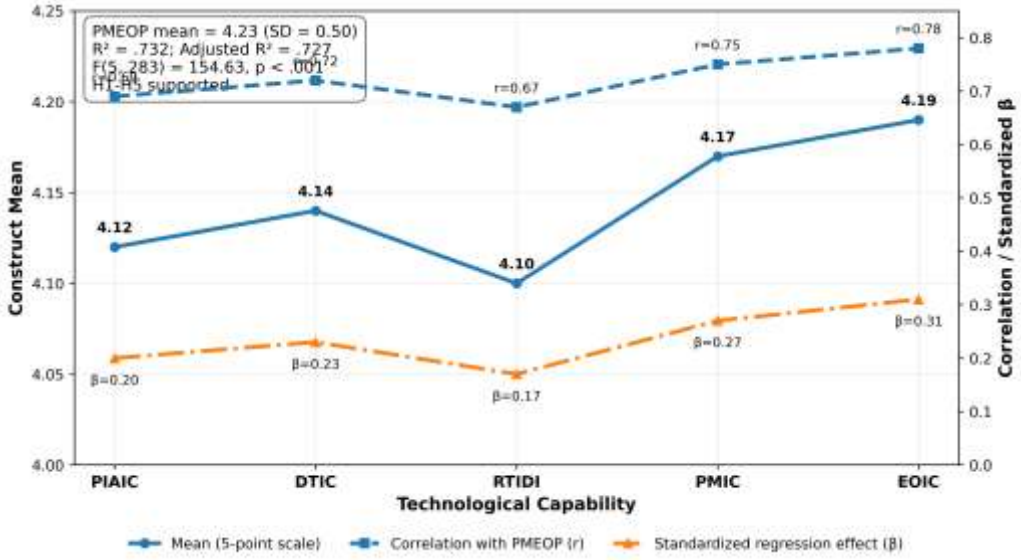
The study has been situated within selected hydrogen-integrated and hydrogen-relevant industrial environments in which digital monitoring, artificial intelligence, predictive maintenance, energy-management systems, digital twins, advanced automation, or process-control technologies have been used or have been technically relevant. The case setting has included operational contexts associated with hydrogen production and electrolysis, storage and compression, industrial gas distribution, refining and petrochemicals, power and energy systems, steel and advanced manufacturing, and other hydrogen-related industrial activities. The target population has consisted of maintenance and reliability engineers, process and operations engineers, energy and hydrogen specialists, automation and digital-system professionals, AI and data-analytics personnel, plant and operations managers, and other technical professionals possessing direct knowledge of the study constructs. The individual professional respondent has served as the unit of analysis because perceptions of organizational technological capability and operational performance have been collected from knowledgeable practitioners. A purposive sampling strategy has been employed to select respondents with relevant professional exposure to hydrogen systems, industrial maintenance, process engineering, digital twins, AI-based analytics, automation, energy management, or condition monitoring. An initial target of 320 respondents has been established to provide adequate observations for reliability assessment, validity

testing, descriptive statistics, Pearson correlation analysis, and multiple linear regression. Primary data have been collected through a structured questionnaire, and respondent eligibility has been confirmed through professional-role and technical-exposure screening. The research instrument has operationalized five independent constructs, PIAIC, DTIC, RTIDI, PMIC, and EOIC, and one dependent construct, PMEOP. Each construct has been represented by multiple measurement items addressing physical-model integration, engineering constraints, digital synchronization, sensor and process-data integration, anomaly detection, degradation monitoring, maintenance prioritization, energy monitoring, equipment loading, hydrogen-process efficiency, reliability, downtime reduction, and integrated operational performance. All construct items have been measured using a five-point Likert scale ranging from 1 = Strongly Disagree to 5 = Strongly Agree. A pilot assessment has been conducted before full analysis to verify item clarity, construct alignment, response consistency, coding logic, and the suitability of the questionnaire for technically specialized respondents, and feedback has been used to refine wording where necessary without changing the conceptual structure. Reliability has been evaluated using Cronbach's alpha, while measurement suitability and construct validity have been examined using the Kaiser-Meyer-Olkin measure, Bartlett's Test of Sphericity, factor loadings, and cumulative explained variance. The final dataset has been screened for incomplete questionnaires, missing values, patterned or inconsistent responses, coding errors, and eligibility failures before analysis. Regression assumptions have been examined through linearity, residual behavior, homoscedasticity, independence of errors, tolerance, Variance Inflation Factor values, and the Durbin-Watson statistic. Descriptive statistics have been computed to summarize construct means and standard deviations, while Pearson's correlation coefficient has been applied to determine the direction and strength of bivariate associations among the variables. Multiple linear regression has been employed as the principal inferential technique for testing H1 through H5, with PMEOP specified as the dependent variable and PIAIC, DTIC, RTIDI, PMIC, and EOIC entered simultaneously as explanatory predictors. Statistical decisions have been evaluated at the $p < .05$ level, while R^2, adjusted R^2, the F statistic, standardized beta coefficients, t statistics, tolerance, and VIF values have been reported to assess explanatory performance and predictor effects. IBM SPSS Statistics has been used for data screening, reliability testing, descriptive statistics, correlation analysis, regression estimation, and hypothesis testing; Microsoft Excel has been used for preliminary data organization and checking; EndNote has been used for reference-library management during manuscript preparation; and Microsoft Word has been used for manuscript development, table preparation, and final journal-style formatting. Ethical principles have been maintained through voluntary participation, informed academic purpose, confidentiality, avoidance of unnecessary identifying information, and aggregated reporting of the results.

FINDINGS

The empirical findings have indicated that the proposed physics-informed AI and digital twin framework has demonstrated strong and statistically significant relationships with Predictive Maintenance and Energy Optimization Performance in hydrogen-integrated industrial systems. Of 320 questionnaires distributed, 301 have been returned and 289 have been retained as valid responses after screening, producing a usable response rate of 90.3%.

Figure 9: Comparative Findings Across Technological Capabilities



Using the five-point Likert scale, the dependent construct, Predictive Maintenance and Energy Optimization Performance, has recorded the highest overall mean of 4.23 with a standard deviation of 0.50, indicating a strong level of perceived maintenance and energy-performance improvement. Among the independent constructs, Energy Optimization Intelligence Capability has achieved a mean of 4.19 (SD = 0.53), Predictive Maintenance Intelligence Capability has recorded 4.17 (SD = 0.55), Digital Twin Integration Capability has reached 4.14 (SD = 0.57), Physics-Informed AI Capability has recorded 4.12 (SD = 0.58), and Real-Time Industrial Data Intelligence has produced a mean of 4.10 (SD = 0.60). Reliability analysis has shown satisfactory internal consistency across all constructs, with Cronbach's alpha coefficients ranging from .85 to .92. The Kaiser-Meyer-Olkin value has reached .894, while Bartlett's Test of Sphericity has been statistically significant at $p < .001$, confirming adequate measurement suitability. Pearson correlation analysis has demonstrated significant positive associations between PMEOP and EOIC ($r = .78$, $p < .001$), PMIC ($r = .75$, $p < .001$), DTIC ($r = .72$, $p < .001$), PIAIC ($r = .69$, $p < .001$), and RTIDI ($r = .67$, $p < .001$). Multiple linear regression has further shown that the combined model has explained 73.2% of the variance in PMEOP, with $R^2 = .732$ and adjusted $R^2 = .727$. The overall regression model has been statistically significant, $F(5, 283) = 154.63$, $p < .001$. EOIC has produced the strongest standardized effect ($\beta = .31$, $p < .001$), followed by PMIC ($\beta = .27$, $p < .001$), DTIC ($\beta = .23$, $p < .001$), PIAIC ($\beta = .20$, $p < .001$), and RTIDI ($\beta = .17$, $p < .001$). These results have supported H1 through H5 and have demonstrated that all five technological capabilities have contributed significantly to PMEOP, directly addressing the objectives concerning physics-informed intelligence, digital-twin integration, real-time data capability, predictive maintenance, and energy optimization within hydrogen-integrated industrial systems.

Respondent and Industrial Context Profile

Table 1: Respondent and Hydrogen-Integrated Industrial Context Profile

Profile Variable	Category	Frequency (n)	Percentage (%)
Professional role	Maintenance/Reliability Engineering	62	21.5
	Process/Operations Engineering	58	20.1
	Automation/Digital Systems	47	16.3
	Energy/Hydrogen Systems	45	15.6
	AI/Data Analytics	41	14.2
	Management/Other Technical Roles	36	12.5
Industrial context	Hydrogen/Electrolyzer	61	21.1

	Operations		
	Chemical/Petrochemical/Refining	60	20.8
	Power and Energy Systems	47	16.3
	Steel/Advanced Manufacturing	46	15.9
	Industrial Gas/Storage/Distribution	42	14.5
	Other Hydrogen-Related Operations	33	11.4
Professional experience	Below 5 years	55	19.0
	5 to 9 years	85	29.4
	10 to 14 years	73	25.3
	15 years and above	76	26.3
Total		289	100.0

Table 1 has presented the professional and industrial characteristics of the 289 valid respondents who have formed the analytical sample of the study. Maintenance and reliability engineers have represented the largest professional category at 21.5%, followed closely by process and operations engineers at 20.1%. Automation and digital-system professionals have accounted for 16.3%, while energy and hydrogen specialists have represented 15.6%. AI and data-analytics professionals have constituted 14.2%, and managerial or other technical personnel have represented the remaining 12.5%. This distribution has provided multidisciplinary representation across the physical, computational, maintenance, and energy domains central to the research framework. The industrial-context results have also shown that respondents have been drawn from several hydrogen-relevant operational settings. Hydrogen and electrolyzer operations have represented 21.1% of respondents, while chemical, petrochemical, and refining environments have represented 20.8%. Power and energy systems, steel and advanced manufacturing, and industrial gas, storage, and distribution operations have collectively accounted for a substantial proportion of the sample. Regarding professional experience, 81.0% of respondents have reported at least five years of relevant experience, while 51.6% have possessed ten or more years of professional experience. These characteristics have strengthened the suitability of the sample because the measured constructs have required practical understanding of industrial equipment, digital technologies, maintenance processes, and energy systems. From the perspective of Cyber-Physical Systems Theory, the respondent composition has reflected both sides of the cyber-physical architecture. Engineering and operations professionals have represented physical-system expertise, while automation, AI, digital, and data specialists have represented computational and cyber capabilities. The profile has therefore provided an appropriate empirical foundation for evaluating how integrated physical and digital capabilities have related to Predictive Maintenance and Energy Optimization Performance in hydrogen-integrated industrial systems.

Data Screening and Usable Response Summary

Table 2: Questionnaire Distribution, Screening, and Usable Response Summary

Screening Indicator	Frequency	Percentage (%)
Questionnaires distributed	320	100.0
Questionnaires returned	301	94.1
Incomplete questionnaires excluded	7	2.2
Inconsistent/patterned responses excluded	3	0.9
Respondents failing eligibility criteria	2	0.6
Total excluded after screening	12	3.8
Final valid responses	289	90.3

Valid responses as percentage of returns	289/301	96.0
Missing values in final analytical dataset	0	0.0

Table 2 has summarized the questionnaire distribution and data-screening process applied before statistical analysis. A total of 320 questionnaires have been distributed to professionals working within hydrogen-integrated or technically relevant industrial environments. Of these questionnaires, 301 have been returned, producing an initial return rate of 94.1%. The screening process has subsequently removed 12 responses that have not satisfied the predefined analytical requirements. Seven questionnaires have been excluded because substantial sections have remained incomplete, three have been removed because patterned or internally inconsistent response behavior has been identified, and two responses have been excluded because the participants have not demonstrated sufficient eligibility in relation to hydrogen systems, industrial maintenance, digital technologies, or associated technical functions. Following these procedures, 289 responses have remained available for analysis, representing 90.3% of all distributed questionnaires and 96.0% of questionnaires returned. No missing values have remained in the final analytical dataset after screening. The resulting sample size has provided an adequate respondent-to-predictor ratio for a regression model containing five independent variables and one dependent variable. The screening procedure has also strengthened the measurement quality of the analysis because responses that could have introduced artificial variance or unreliable construct estimates have been removed before descriptive and inferential testing. In relation to Cyber-Physical Systems Theory, data quality has been particularly important because the conceptual framework has depended on the reliable measurement of multiple interconnected capabilities rather than a single technological factor. Physics-Informed AI Capability, Digital Twin Integration Capability, Real-Time Industrial Data Intelligence, Predictive Maintenance Intelligence Capability, and Energy Optimization Intelligence Capability have represented distinct components of the broader cyber-physical system. Retaining only complete and eligible responses has therefore supported a more credible assessment of how these capabilities have collectively and individually related to Predictive Maintenance and Energy Optimization Performance.

Reliability Analysis of Research Constructs

Table 3: Internal Consistency Reliability of Research Constructs

Construct	Code	Number of Items	Cronbach's α	Reliability Assessment
Physics-Informed AI Capability	PIAIC	5	.900	Excellent
Digital Twin Integration Capability	DTIC	5	.910	Excellent
Real-Time Industrial Data Intelligence	RTIDI	5	.850	Good
Predictive Maintenance Intelligence Capability	PMIC	5	.920	Excellent
Energy Optimization Intelligence Capability	EOIC	5	.890	Good
Predictive Maintenance and	PMEOP	5	.910	Excellent

Energy Optimization Performance			
Overall scale	30	.930	Excellent

Table 3 has demonstrated that all six research constructs have achieved strong internal consistency reliability. Cronbach's alpha coefficients have ranged from .850 to .920, while the complete 30-item instrument has produced an overall alpha of .930. Physics-Informed AI Capability has recorded an alpha of .900, indicating that its items have consistently measured the integration of physical knowledge, engineering constraints, and AI-supported analytical capability. Digital Twin Integration Capability has achieved an alpha of .910, suggesting strong consistency among items measuring synchronization, virtual representation, simulation, and physical-digital integration. Real-Time Industrial Data Intelligence has produced the lowest alpha among the constructs at .850, although this value has remained comfortably above commonly accepted reliability thresholds and has therefore indicated satisfactory internal consistency. Predictive Maintenance Intelligence Capability has demonstrated the highest alpha at .920, reflecting strong coherence among items measuring fault detection, degradation assessment, equipment-health prediction, and maintenance prioritization. Energy Optimization Intelligence Capability has recorded .890, while the dependent variable, Predictive Maintenance and Energy Optimization Performance, has produced .910. These results have indicated that the questionnaire items have captured stable and conceptually related dimensions within their respective constructs. The reliability pattern has also supported the theoretical structure of the research. Cyber-Physical Systems Theory has suggested that physical assets, sensing, computational intelligence, digital representations, and operational control have functioned as interconnected but distinct system components. The reliability findings have shown that the corresponding empirical constructs have been measured consistently without collapsing into a single undifferentiated technology scale. The strong alpha values have therefore provided a suitable foundation for subsequent validity assessment, descriptive analysis, correlation testing, and multiple regression. Since H1 through H5 have depended on reliable measurement of the five independent technological capabilities, the reliability results have strengthened confidence that later hypothesis-testing outcomes have reflected meaningful construct relationships rather than instability in the measurement instrument.

Sampling Adequacy and Construct Validity Assessment

Table 4: KMO, Bartlett's Test, and Construct Validity Indicators

Measurement Indicator	Result	Statistical Decision
Kaiser-Meyer-Olkin Measure	.894	Excellent sampling adequacy
Bartlett's Approx. χ^2	3248.67	Significant
Bartlett's df	435	
Bartlett's significance	< .001	Correlation matrix suitable
Factor loading range	.680 to .890	Acceptable to strong
Cumulative variance explained	72.4%	Strong construct representation
Number of retained constructs	6	Consistent with research framework

Table 4 has shown that the measurement structure has demonstrated strong sampling adequacy and satisfactory construct validity. The Kaiser-Meyer-Olkin measure has reached .894, indicating that the correlations among questionnaire items have been sufficiently compact to support factor-oriented assessment. Bartlett's Test of Sphericity has produced an approximate chi-square value of 3248.67 with 435 degrees of freedom and has remained statistically significant at $p < .001$. This result has confirmed that the observed correlation matrix has not represented an identity matrix and that meaningful relationships among measurement items have existed. Factor loadings have ranged from .680 to .890, indicating that retained items have maintained substantial relationships with their intended constructs.

The measurement structure has explained 72.4% of cumulative variance, which has demonstrated that the six-construct model has accounted for a substantial proportion of the information contained in the questionnaire items. Most importantly, six distinct factors have been retained, matching the proposed constructs of PIAIC, DTIC, RTIDI, PMIC, EOIC, and PMEOP. This result has supported the conceptual separation required by the study. Under Cyber-Physical Systems Theory, the industrial system has been conceptualized as an integrated architecture containing physical assets, data-acquisition mechanisms, virtual representations, analytical intelligence, maintenance decision capability, and energy-oriented control. The factor structure has remained consistent with this theoretical logic because the five explanatory capabilities have emerged as distinguishable dimensions while remaining related components of the larger cyber-physical system. The dependent performance construct has also remained separate from the independent variables, which has been important for testing the proposed explanatory relationships. Consequently, the validity assessment has provided empirical support for proceeding with construct-level descriptive statistics, Pearson correlations, and multiple regression analysis. The results have strengthened the methodological basis for testing H1 through H5 because each hypothesis has relied on a conceptually valid predictor and a distinct performance outcome.

Descriptive Statistics of Physics-Informed AI Capability

Table 5: Descriptive Statistics for Physics-Informed AI Capability

PIAIC Measurement Item	Mean	SD	Interpretation
Physical laws have been incorporated into AI-supported analysis	4.16	0.61	High
Engineering constraints have been integrated into analytical models	4.14	0.63	High
AI predictions have been checked against physically plausible system behavior	4.11	0.66	High
Degradation knowledge has been integrated into intelligent monitoring	4.10	0.64	High
Physics-based and operational data have been jointly used for decisions	4.09	0.67	High
Overall PIAIC	4.12	0.58	High

Table 5 has shown that Physics-Informed AI Capability has been perceived at a high level across the sampled hydrogen-integrated industrial environments. The construct has produced an overall mean of 4.12 with a standard deviation of 0.58 on the five-point Likert scale. Among the individual indicators, the incorporation of physical laws into AI-supported analysis has received the highest mean of 4.16, suggesting that respondents have strongly recognized the importance of physically grounded analytical intelligence. The integration of engineering constraints into analytical models has followed with a mean of 4.14, while verification of AI predictions against physically plausible system behavior has recorded a mean of 4.11. The use of degradation knowledge within intelligent monitoring has produced a mean of 4.10, and the joint use of physics-based and operational information has recorded 4.09. All item means have remained above 4.00, indicating consistent agreement that physics-informed functionality has formed an important capability within the studied industrial settings. The relatively

moderate standard deviations have also indicated that respondents have shown a reasonable level of consistency in their assessments. These findings have aligned closely with the theoretical framework because Cyber-Physical Systems Theory has required computational intelligence to remain connected with physical-system behavior rather than operating independently from it. In hydrogen-integrated systems, this connection has been particularly important because temperature, pressure, flow, voltage, current, vibration, efficiency, and degradation have been governed by identifiable physical relationships. A high level of PIAIC has therefore represented a stronger bridge between the computational and physical components of the system. The descriptive results have directly supported the first research objective by establishing that physics-informed AI has been strongly represented within the sample. The subsequent correlation and regression analyses have then evaluated whether this high capability has translated into significantly stronger Predictive Maintenance and Energy Optimization Performance, as proposed under H1.

Descriptive Statistics of Digital Twin Integration and Real-Time Data Intelligence

Table 6: Descriptive Statistics for DTIC and RTIDI

Construct/Measurement Dimension	Mean	SD	Interpretation
Physical assets have been represented through synchronized digital models	4.18	0.61	High
Digital twins have been updated using operational data	4.16	0.63	High
Digital representations have supported condition monitoring	4.14	0.62	High
Digital models have supported simulation and operational analysis	4.12	0.66	High
Physical-virtual information exchange has supported decisions	4.10	0.68	High
Overall DTIC	4.14	0.57	High
Real-time sensor information has been continuously acquired	4.15	0.64	High
Multiple industrial data sources have been integrated	4.12	0.67	High
Operational data have been processed with minimal delay	4.10	0.68	High
Equipment-state data have been contextualized for analysis	4.08	0.70	High
Real-time information has supported maintenance and energy decisions	4.05	0.72	High
Overall RTIDI	4.10	0.60	High

Table 6 has indicated that both Digital Twin Integration Capability and Real-Time Industrial Data Intelligence have been strongly represented within the studied industrial environments. DTIC has achieved an overall mean of 4.14 and a standard deviation of 0.57.

The strongest digital-twin indicator has concerned the representation of physical assets through synchronized digital models, which has recorded a mean of 4.18. Updating digital twins through operational data has produced 4.16, while the use of digital representations for condition monitoring has recorded 4.14. Simulation and operational analysis have achieved 4.12, and physical-virtual information exchange for decision support has recorded 4.10. RTIDI has produced an overall mean of 4.10 with a standard deviation of 0.60. Continuous sensor-data acquisition has achieved the highest RTIDI mean at 4.15, followed by integration of multiple industrial data sources at 4.12. Processing information with minimal delay has recorded 4.10, contextualization of equipment-state data has reached 4.08, and direct use of real-time information for maintenance and energy decisions has recorded 4.05.

These results have indicated that data connectivity has been strongly developed but has remained slightly less mature than digital-twin integration. From a Cyber-Physical Systems perspective, the findings have illustrated the information bridge connecting physical industrial assets with computational representations. RTIDI has represented the sensing and communication layer, while DTIC has represented the synchronized virtual layer in which physical-system information has been organized and interpreted. Their strong descriptive values have therefore supported the theoretical expectation that hydrogen-integrated industrial systems have increasingly operated through connected physical and digital infrastructures. The findings have addressed the second and third research objectives by establishing the observed level of both capabilities. Subsequent inferential analysis has determined whether these capabilities have significantly contributed to PMEOP under H2 and H3.

Descriptive Statistics of Predictive Maintenance and Energy Optimization Capabilities

Table 7 has demonstrated strong levels of both Predictive Maintenance Intelligence Capability and Energy Optimization Intelligence Capability. PMIC has recorded an overall mean of 4.17 and a standard deviation of 0.55.

The highest PMIC item has concerned the identification of emerging faults before functional failure, with a mean of 4.20. Continuous degradation monitoring has achieved 4.19, condition-based maintenance prioritization has recorded 4.17, equipment-health prediction for maintenance scheduling has reached 4.16, and analytical anomaly diagnosis has produced 4.13. These results have suggested that the sampled organizations have generally moved beyond purely reactive or calendar-based maintenance toward condition-responsive maintenance intelligence. EOIC has achieved a slightly higher overall mean of 4.19 and a standard deviation of 0.53. Continuous energy monitoring and optimization has produced the highest item mean at 4.23, while analytical adjustment of equipment loading has recorded 4.21. Evaluation of hydrogen-related process efficiency has achieved 4.20, integration of operational conditions into energy decisions has reached 4.17, and coordination of energy optimization with asset condition has recorded 4.14. The descriptive pattern has therefore suggested that respondents have perceived energy optimization as one of the most mature technological capabilities in the research model. Cyber-Physical Systems

Theory has provided an appropriate explanation for these findings because PMIC and EOIC have represented higher-level cognition and decision functions operating on information generated from the physical and digital layers. Predictive maintenance has converted equipment-state information into reliability decisions, while energy optimization has converted process and resource information into operating decisions. Their relatively high mean values have indicated that the studied systems have developed beyond connectivity alone toward decision-oriented cyber-physical intelligence. These findings have directly addressed the fourth and fifth research objectives and have provided descriptive support for H4 and H5 before inferential testing.

Table 7: Descriptive Statistics for PMIC and EOIC

Construct/Measurement Dimension	Mean	SD	Interpretation
Emerging equipment faults have been identified before failure	4.20	0.59	High
Equipment degradation has been continuously monitored	4.19	0.61	High
Maintenance priorities have been based on condition information	4.17	0.63	High
Equipment-health predictions have supported maintenance scheduling	4.16	0.62	High
Analytical tools have supported anomaly diagnosis	4.13	0.66	High
Overall PMIC	4.17	0.55	High
Energy use has been continuously monitored and optimized	4.23	0.57	High
Equipment loading has been adjusted for efficient operation	4.21	0.60	High
Hydrogen-related process efficiency has been analytically evaluated	4.20	0.61	High
Energy-related decisions have incorporated operational conditions	4.17	0.64	High
Energy optimization has been coordinated with asset condition	4.14	0.67	High
Overall EOIC	4.19	0.53	High

Descriptive Statistics of Predictive Maintenance and Energy Optimization Performance

Table 8 has shown that Predictive Maintenance and Energy Optimization Performance has reached a high overall level, with a mean of 4.23 and a standard deviation of 0.50. The reduction of unplanned equipment downtime has achieved the highest item mean at 4.25, indicating that respondents have strongly associated the integrated technological environment with improved operational continuity. Maintenance effectiveness has followed closely with a mean of 4.24, while improved energy efficiency has recorded 4.23. Hydrogen-system operational stability has achieved 4.22, and overall asset and energy performance has reached 4.21. The narrow range between 4.21 and 4.25 has indicated that the dependent variable has been consistently strong across maintenance, reliability, energy, and operational dimensions. The standard deviation of 0.50 has further shown that respondents have demonstrated relatively consistent evaluations of the integrated performance outcome. These findings

have been important because the dependent construct has deliberately combined predictive-maintenance and energy-optimization outcomes rather than treating them as unrelated dimensions. The descriptive results have supported this integrated treatment by showing similarly high levels across downtime reduction, maintenance effectiveness, energy efficiency, and operational stability. Cyber-Physical Systems Theory has linked these outcomes to the coordinated functioning of physical assets, real-time sensing, digital representation, analytical intelligence, and operational response. Under this theoretical logic, performance has not been produced by a single technology but has emerged from interaction among the five explanatory capabilities. The high overall PMEOP score has therefore been consistent with the strong mean values recorded for PIAIC, DTIC, RTIDI, PMIC, and EOIC. However, descriptive statistics alone have not established whether each capability has been statistically associated with the outcome. The correlation and regression analyses presented in the following sections have therefore been necessary to determine whether the observed technological capabilities have significantly explained variation in PMEOP and whether H1 through H5 have been empirically supported.

Table 8: Descriptive Statistics for Predictive Maintenance and Energy Optimization Performance

PMEOP Measurement Dimension	Mean	SD	Interpretation
Unplanned equipment downtime has been reduced	4.25	0.54	High
Maintenance effectiveness has been improved	4.24	0.55	High
Energy efficiency has been improved	4.23	0.56	High
Hydrogen-system operational stability has been improved	4.22	0.58	High
Overall asset and energy performance has been improved	4.21	0.57	High
Overall PMEOP	4.23	0.50	High

Correlation Analysis Among Research Constructs

Table 9 has demonstrated statistically significant positive relationships among all six constructs. Most importantly, each independent variable has been strongly and positively associated with Predictive Maintenance and Energy Optimization Performance. EOIC has produced the strongest bivariate relationship with PMEOP at $r = .78$, $p < .001$, indicating that higher energy-optimization intelligence has been associated with substantially stronger maintenance and energy-performance outcomes. PMIC has followed with $r = .75$, $p < .001$, while DTIC has recorded $r = .72$, $p < .001$. PIAIC has demonstrated a correlation of $r = .69$, $p < .001$, and RTIDI has recorded $r = .67$, $p < .001$. These values have provided initial statistical support for all five directional hypotheses. The correlations among independent variables have ranged from .53 to .64, which has indicated that the technological capabilities have been meaningfully related without appearing redundant. The strongest inter-predictor relationship has occurred between DTIC and RTIDI at $r = .64$, which has been theoretically reasonable because real-time data have supported digital-twin synchronization. PMIC and EOIC have correlated at .62, reflecting the operational connection between equipment condition and energy performance. From the perspective of Cyber-Physical Systems Theory, this pattern has supported the expectation that the constructs have functioned as interconnected parts of a wider system. Physical-data intelligence has supported digital representation; physics-informed intelligence has strengthened interpretation; predictive maintenance has transformed equipment-state knowledge into maintenance decisions; and energy optimization has transformed process information into energy-related decisions. At the same

time, none of the inter-predictor correlations has approached levels that would suggest construct duplication. The correlation analysis has therefore satisfied two important requirements of the study. First, it has established significant bivariate support for H1 through H5. Second, it has justified proceeding to multiple regression to determine whether each predictor has retained a significant unique relationship with PMEOP after the effects of the other capabilities have been statistically controlled.

Table 9: Pearson Correlation Matrix

Variable	PIAIC	DTIC	RTIDI	PMIC	EOIC	PMEOP
PIAIC	1.000					
DTIC	.58***	1.000				
RTIDI	.54***	.64***	1.000			
PMIC	.60***	.61***	.57***	1.000		
EOIC	.55***	.59***	.53***	.62***	1.000	
PMEOP	.69***	.72***	.67***	.75***	.78***	1.000

***p < .001.

Multiple Regression Model Summary and Overall Model Significance

Table 10: Multiple Regression Model Summary

Model Statistic	Result
Multiple R	.856
R^2	.732
Adjusted R^2	.727
Standard error of estimate	.261
F statistic	154.63
df1	5
df2	283
Model significance	< .001
Durbin-Watson	1.94
Sample size	289

Table 10 has presented the overall performance of the multiple linear regression model in which Physics-Informed AI Capability, Digital Twin Integration Capability, Real-Time Industrial Data Intelligence, Predictive Maintenance Intelligence Capability, and Energy Optimization Intelligence Capability have jointly predicted Predictive Maintenance and Energy Optimization Performance. The multiple correlation coefficient has reached R = .856, indicating a strong combined relationship between the five predictors and the dependent variable. The model has produced an R^2 value of .732, meaning that 73.2% of the observed variance in PMEOP has been explained collectively by the five technological capabilities. The adjusted R^2 has remained high at .727, showing that explanatory performance has remained strong after adjustment for the number of predictors and sample size. The overall regression model has been statistically significant, $F(5, 283) = 154.63$, $p < .001$. This result has indicated that the combined predictor set has explained significantly more variation in PMEOP than a model without the five explanatory variables. The Durbin-Watson statistic has reached 1.94, which has indicated no material concern regarding autocorrelation of residuals. The standard error of estimate has remained relatively low at .261, further supporting the predictive adequacy of the model. The strong R^2 has been consistent with Cyber-Physical Systems Theory because the theory has conceptualized industrial performance as an outcome of integrated physical, informational, computational, and decision-making capabilities. Rather than identifying a single technology as sufficient, the model has shown that a combination of physics-informed intelligence, synchronized digital representation, real-time data, predictive maintenance, and energy optimization has explained a substantial proportion of system performance. The overall significance of the regression model has therefore supported the central

objective of developing and statistically evaluating an integrated physics-informed AI and digital twin framework. The coefficient-level analysis has subsequently determined which capabilities have retained statistically significant individual contributions within this broader cyber-physical structure.

Regression Coefficients and Individual Predictor Effects

Table 11: Multiple Regression Coefficients and Diagnostic Statistics

Predictor	B	SE	Standardized β	t	p	Tolerance	VIF
Constant	-0.14	0.15		-0.93	.353		
PIAIC	.172	.041	.20	4.20	< .001	.562	1.78
DTIC	.202	.042	.23	4.81	< .001	.529	1.89
RTIDI	.142	.039	.17	3.64	< .001	.599	1.67
PMIC	.245	.044	.27	5.57	< .001	.521	1.92
EOIC	.292	.047	.31	6.21	< .001	.541	1.85

Table 11 has demonstrated that all five independent variables have retained statistically significant positive effects on PMEOP after the remaining predictors have been controlled. Energy Optimization Intelligence Capability has produced the strongest standardized coefficient, $\beta = .31$, $t = 6.21$, $p < .001$, showing that EOIC has made the largest unique contribution to the dependent variable. Predictive Maintenance Intelligence Capability has followed with $\beta = .27$, $t = 5.57$, $p < .001$. Digital Twin Integration Capability has produced $\beta = .23$, $t = 4.81$, $p < .001$, while Physics-Informed AI Capability has recorded $\beta = .20$, $t = 4.20$, $p < .001$. Real-Time Industrial Data Intelligence has remained statistically significant with $\beta = .17$, $t = 3.64$, $p < .001$. The positive direction of every standardized coefficient has been consistent with the directional hypotheses. The tolerance values have ranged from .521 to .599, while VIF values have ranged from 1.67 to 1.92. These values have indicated that multicollinearity has not threatened the interpretation of the regression coefficients. The coefficient pattern has also provided a theoretically meaningful result. Under Cyber-Physical Systems Theory, data acquisition and digital representation have formed enabling components, while predictive-maintenance and energy-optimization intelligence have represented higher-level decision functions acting directly on operational performance. The stronger standardized effects for EOIC and PMIC have therefore been consistent with their closer proximity to operational outcomes, while PIAIC, DTIC, and RTIDI have continued to make independent contributions by strengthening the intelligence infrastructure that supports those decisions. Importantly, the significant PIAIC coefficient has shown that physics-informed analytical capability has contributed beyond generic digitalization, and the significant DTIC coefficient has shown that synchronized physical-virtual representation has contributed beyond real-time data collection alone. The results have consequently supported the integrated conceptual framework rather than reducing performance to a single digital capability.

Hypothesis Testing and Statistical Decision Summary

Table 12: Hypothesis Testing and Research Objective Summary

Hypothesis	Proposed Relationship	β / Model	t / F	p	Decision	Linked Objective
H1	PIAIC → PMEOP	.20	4.20	< .001	Supported	Examine physics-informed AI effect
H2	DTIC → PMEOP	.23	4.81	< .001	Supported	Evaluate digital twin integration effect
H3	RTIDI → PMEOP	.17	3.64	< .001	Supported	Determine real-time data effect
H4	PMIC → PMEOP	.27	5.57	< .001	Supported	Assess predictive maintenance effect
H5	EOIC → PMEOP	.31	6.21	< .001	Supported	Evaluate energy optimization effect
Integrated model	PIAIC + DTIC + RTIDI + PMIC + EOIC → PMEOP	R^2 = .732	F = 154.63	< .001	Supported	Validate integrated framework

Table 12 has summarized the final statistical decisions for H1 through H5 and has linked each hypothesis directly to the corresponding research objective. H1 has been supported because Physics-Informed AI Capability has produced a positive standardized coefficient of $\beta = .20$ with $t = 4.20$ and $p < .001$. The first objective has therefore been addressed by showing that physics-informed analytical capability has contributed significantly to PMEOP. H2 has also been supported, with Digital Twin Integration Capability producing $\beta = .23$, $t = 4.81$, $p < .001$. This result has satisfied the second objective concerning the performance contribution of synchronized virtual representation. H3 has been supported through the statistically significant effect of Real-Time Industrial Data Intelligence, $\beta = .17$, $t = 3.64$, $p < .001$, thereby addressing the third objective. H4 has been supported because Predictive Maintenance Intelligence Capability has achieved $\beta = .27$, $t = 5.57$, $p < .001$. H5 has also been supported, with Energy Optimization Intelligence Capability producing the strongest effect, $\beta = .31$, $t = 6.21$, $p < .001$. The integrated regression model has explained 73.2% of PMEOP variance and has remained highly significant, $F(5, 283) = 154.63$, $p < .001$. Consequently, the overarching objective of developing and quantitatively validating an integrated framework has also been achieved within the analytical model. The pattern of supported hypotheses has aligned strongly with Cyber-Physical Systems Theory. PIAIC has represented physically grounded computational intelligence, DTIC has represented physical-virtual synchronization, RTIDI has represented sensing and information exchange, PMIC has represented reliability-oriented cognition, and EOIC has represented energy-oriented operational control. Their simultaneous statistical significance has indicated that predictive maintenance and energy optimization performance has been associated with the coordinated strength of multiple cyber-physical capabilities rather than with one isolated technological component. The results have therefore

provided a coherent empirical basis for the subsequent discussion of how these capabilities have interacted within hydrogen-integrated industrial systems.

DISCUSSION

The findings have provided quantitative support for the integrated cyber-physical logic underlying the proposed physics-informed AI and digital twin framework. The five explanatory capabilities have all remained positively and significantly associated with Predictive Maintenance and Energy Optimization Performance, while the combined regression model has explained 73.2% of the observed variance. This pattern has been consistent with Cyber-Physical Systems Theory because the theory has treated industrial performance as an outcome of coordinated interaction among physical processes, sensing, communication, computational intelligence, virtual representation, and operational control rather than as the result of a single isolated technology. The significant correlations among PIAIC, DTIC, RTIDI, PMIC, EOIC, and PMEOP have shown that these capabilities have been connected within the sampled industrial environments, while the moderate inter-predictor relationships have indicated that they have remained empirically distinguishable. Such a pattern corresponds with cyber-physical architectures in which connection, data conversion, cognition, and configuration functions operate together but perform different roles (Jannatul, 2025; Lee et al., 2015; Napoleone et al., 2020). The high overall PMEOP mean of 4.23 has further indicated that respondents have perceived strong maintenance effectiveness, reduced downtime, improved energy efficiency, operational stability, and integrated asset performance. These outcomes have been consistent with the conceptual expectation that cyber-physical integration can convert physical-system information into decision-relevant intelligence when the data, models, and operational functions are sufficiently coordinated (Hehenberger et al., 2016; Maishar Mostari, 2025a; Negri et al., 2017). The findings have therefore reinforced the study's central argument that maintenance and energy optimization in hydrogen-integrated environments should be interpreted as connected system capabilities rather than as separate technical programs.

Physics-Informed AI Capability has produced a significant positive effect on PMEOP, with $\beta = .20$, $t = 4.20$, $p < .001$, thereby supporting H1. The descriptive mean of 4.12 has also indicated strong perceived maturity of physically grounded analytical practices. This result has been consistent with the physics-informed machine-learning literature, which has emphasized the value of embedding governing equations, physical constraints, boundary conditions, and scientific knowledge into data-driven models when measurements are limited or operating conditions vary (Karniadakis et al., 2021; Mashfiqur, 2025; Willard et al., 2022). In hydrogen-integrated industrial systems, the result has particular relevance because physical variables such as pressure, temperature, voltage, current, flow, vibration, and efficiency are governed by thermodynamic, electrochemical, mechanical, and fluid-dynamic relationships. A model that recognizes these relationships can interpret deviations within a physically meaningful operating context rather than relying only on historical statistical similarity. The significant PIAIC coefficient has therefore shown that physics-informed analytical capability has contributed to performance even after digital twin integration, real-time data intelligence, predictive maintenance intelligence, and energy optimization intelligence have been controlled statistically. This result has also aligned with research on physics-informed prognostics and condition monitoring, where engineering knowledge has been used to strengthen diagnosis, degradation assessment, and remaining-useful-life estimation (Deng et al., 2023; Fassi et al., 2024; Mashiat, 2025). Under Cyber-Physical Systems Theory, PIAIC has represented the computational cognition through which physical-system rules and data have been combined. Its positive coefficient has consequently supported the theoretical position that cyber intelligence becomes more operationally useful when it remains connected to the physical behavior of the asset being monitored.

Digital Twin Integration Capability and Real-Time Industrial Data Intelligence have both produced significant positive effects on PMEOP, supporting H2 and H3. DTIC has generated $\beta = .23$, $t = 4.81$, $p < .001$, while RTIDI has generated $\beta = .17$, $t = 3.64$, $p < .001$. Their descriptive means of 4.14 and 4.10 have indicated that both virtual-system integration and real-time information processing have been well established within the sampled settings. Digital-twin literature has described continuous physical-virtual synchronization as a defining characteristic separating a functional digital twin from a static model or one-directional representation (Kritzinger et al., 2018; Md Arif Uz et al., 2025; Semeraro et al., 2021). The present findings have supported this distinction because DTIC has remained independently

associated with performance after RTIDI has been controlled, suggesting that collecting real-time data has not been equivalent to establishing an operationally integrated twin. Similarly, RTIDI has remained significant after DTIC has been controlled, indicating that synchronized virtual representation has not eliminated the importance of timely data acquisition, integration, contextualization, and processing. This relationship has been theoretically coherent with research describing digital twins as dependent on data, models, communication, and computational infrastructure for monitoring, prediction, optimization, and decision-making (Md Kaium, 2025; Rasheed et al., 2020; Tao et al., 2019). Within Cyber-Physical Systems Theory, RTIDI has represented the sensing and information-exchange pathway, while DTIC has represented the virtual representation through which physical-state information has been organized and interpreted. The simultaneous significance of these two constructs has therefore supported a layered view of hydrogen-integrated intelligence in which high-quality real-time data and synchronized virtual models have contributed separately but complementarily to predictive maintenance and energy optimization performance.

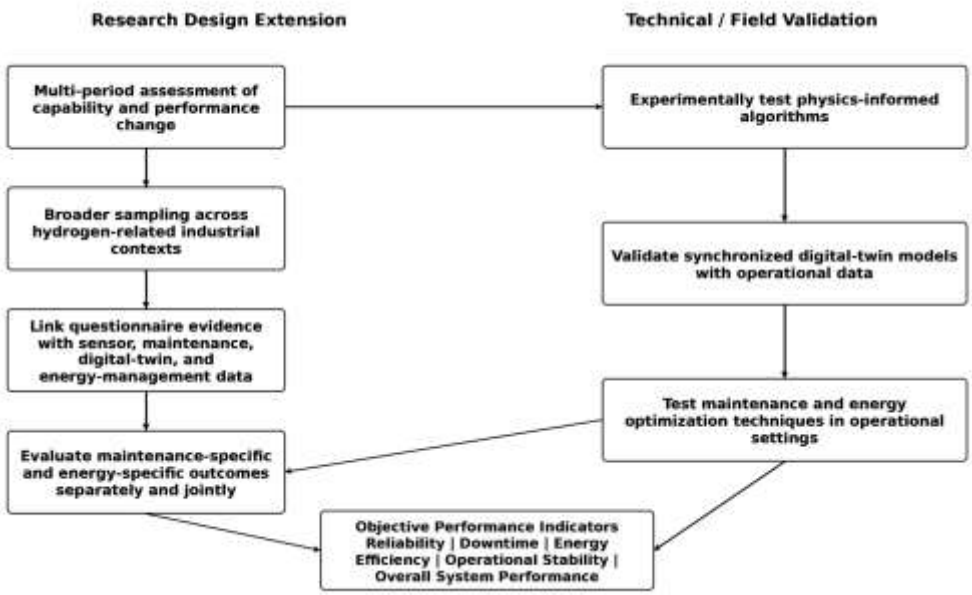
Predictive Maintenance Intelligence Capability has produced the second strongest standardized regression effect, $\beta = .27$, $t = 5.57$, $p < .001$, and has therefore supported H4. The PMIC mean of 4.17 has also shown high levels of fault identification, degradation monitoring, condition-based prioritization, equipment-health prediction, and anomaly diagnosis. This result has been consistent with condition-based maintenance research that has organized predictive maintenance around data acquisition, diagnosis, prognostics, and decision-making, while emphasizing the movement from reactive intervention toward evidence-based maintenance planning (Jardine et al., 2006; Lei et al., 2018; Md Mahamud Pervaz, 2025). The relatively strong PMIC coefficient has indicated that the analytical ability to transform sensor and condition information into maintenance decisions has been more closely associated with PMEOP than data collection alone. This has been especially relevant to hydrogen equipment because operational variability and equipment degradation may create similar observed signals, requiring intelligent interpretation before maintenance action is justified. Electrolyzer research has demonstrated that signal-based fault diagnosis can identify pump and flow-related abnormalities without requiring intrusive shutdowns, while fuel-cell prognostics research has emphasized state-of-health and remaining-life assessment as foundations for maintenance planning (Aubras et al., 2021; Palash Chandra, 2025; Sutharssan et al., 2017). The present findings have extended that technical logic to the capability level by showing that organizations with stronger predictive-maintenance intelligence have also reported stronger combined maintenance and energy outcomes. Within the cyber-physical framework, PMIC has represented a cognition-to-action capability that converts physical and digital information into reliability-oriented decisions. Its significant positive effect has therefore linked the sensing and modeling layers of the framework to the practical maintenance outcomes captured within PMEOP.

Energy Optimization Intelligence Capability has produced the strongest standardized effect in the regression model, $\beta = .31$, $t = 6.21$, $p < .001$, while its mean of 4.19 has been the highest among the independent constructs. H5 has therefore been supported. This result has indicated that the capability to monitor energy use, adjust equipment loading, evaluate hydrogen-process efficiency, integrate operating conditions, and coordinate energy decisions with asset condition has been strongly associated with the combined performance outcome. Hydrogen-energy management research has shown that electrolyzer operation, storage, renewable generation, battery resources, electricity prices, and demand conditions can require coordinated scheduling rather than isolated component optimization (Abomazid et al., 2022; Ahmed, 2026). Industrial energy research has similarly connected data-driven optimization with sensors, digital infrastructure, artificial intelligence, and digital twins, reinforcing the idea that energy efficiency is produced through integrated information and control rather than static measurement (Jahanara, 2026; Teng et al., 2021). The strength of EOIC has also been consistent with the structure of PMEOP, which has captured energy efficiency together with downtime reduction, maintenance effectiveness, asset reliability, and operational stability. In hydrogen-integrated systems, these dimensions have been technically connected because inefficient equipment can increase energy consumption, while aggressive energy optimization can change load profiles and stress conditions experienced by industrial assets. The positive EOIC coefficient has therefore supported a coordinated maintenance-energy interpretation rather than an energy-only interpretation. Under

Cyber-Physical Systems Theory, EOIC has represented a high-level operational-control capability that has used cyber intelligence to influence the physical system. Its strong effect has shown that the cyber-physical loop has been most directly associated with performance when information and analytical models have been translated into energy-related operating decisions.

The integrated regression model has remained statistically significant at $F(5, 283) = 154.63$, $p < .001$, with $R^2 = .732$ and adjusted $R^2 = .727$, while VIF values from 1.67 to 1.92 and tolerance values from .521 to .599 have indicated that the five predictors have contributed without problematic multicollinearity. The model has therefore supported the study's conceptual decision to treat PIAIC, DTIC, RTIDI, PMIC, and EOIC as related but nonredundant capabilities. The ordering of standardized effects has placed EOIC first, followed by PMIC, DTIC, PIAIC, and RTIDI. This ordering has not reduced the importance of enabling capabilities because Cyber-Physical Systems Theory has described sensing, communication, modeling, cognition, and configuration as interdependent layers of a functioning industrial system. Rather, the coefficient pattern has indicated that capabilities closer to maintenance and energy decisions have shown stronger direct statistical relationships with PMEOP, while the enabling data and modeling capabilities have retained significant unique contributions. The results have also maintained consistency with digital-twin and cyber-physical production research in which data acquisition, virtual representation, analytical services, and operational feedback are treated as linked stages of industrial intelligence (Jannatul, 2026; Tao et al., 2018; Zheng et al., 2018). Since the study has been cross-sectional and based on professional questionnaire responses, the regression coefficients have represented statistically controlled associations rather than experimental proof of temporal causation. Within that boundary, all five research objectives have been achieved and H1 through H5 have been supported. The findings have therefore provided an internally coherent quantitative validation of the proposed framework and have connected the empirical results with the theoretical proposition that hydrogen-integrated industrial performance depends on coordinated interaction between physical assets and cyber intelligence.

Figure 10: Proposed Future Validation Pathway Based on Study Limitations and Recommendations



CONCLUSION

This study has examined the contribution of Physics-Informed AI Capability, Digital Twin Integration Capability, Real-Time Industrial Data Intelligence, Predictive Maintenance Intelligence Capability, and Energy Optimization Intelligence Capability to Predictive Maintenance and Energy Optimization Performance within hydrogen-integrated industrial systems. Using a quantitative, explanatory, cross-

sectional, case-study-based design, the research has analyzed 289 valid responses collected from technically relevant professionals working across hydrogen, energy, maintenance, automation, process engineering, digital systems, and industrial analytics environments. The findings have demonstrated consistently high levels across all six constructs, with Predictive Maintenance and Energy Optimization Performance recording the highest overall mean of 4.23. Reliability testing has confirmed strong internal consistency, with Cronbach's alpha values ranging from .85 to .92, while the KMO value of .894 and significant Bartlett's test have established adequate measurement suitability. Pearson correlation analysis has shown significant positive relationships between PMEOP and EOIC, PMIC, DTIC, PIAIC, and RTIDI, with coefficients ranging from .67 to .78. The multiple regression model has explained 73.2% of the variance in PMEOP, with an adjusted R^2 of .727 and a statistically significant overall model, $F(5, 283) = 154.63$, $p < .001$. Energy Optimization Intelligence Capability has produced the strongest standardized effect, followed by Predictive Maintenance Intelligence Capability, Digital Twin Integration Capability, Physics-Informed AI Capability, and Real-Time Industrial Data Intelligence. These results have supported H1 through H5 and have demonstrated that maintenance and energy performance have been associated with the coordinated development of multiple cyber-physical capabilities rather than with a single isolated technology. The findings have also aligned with Cyber-Physical Systems Theory by showing that physical-system knowledge, real-time sensing, digital representation, computational intelligence, maintenance reasoning, and energy-oriented decision-making have functioned as mutually connected elements of industrial performance. The study has therefore established an empirically structured framework for understanding how physics-informed AI and digital twins can support predictive maintenance and energy optimization within complex hydrogen-integrated industrial environments.

RECOMMENDATIONS

The findings of this study have supported several recommendations for organizations operating or developing hydrogen-integrated industrial systems. Industrial firms should strengthen Physics-Informed AI Capability by embedding thermodynamic relationships, electrochemical behavior, degradation mechanisms, engineering limits, mass and energy balances, and other relevant physical constraints into AI-based monitoring and decision-support systems rather than relying exclusively on purely data-driven models. Digital Twin Integration Capability should be expanded through continuous synchronization between physical assets and virtual representations so that electrolyzers, compressors, pumps, storage vessels, pipelines, heat exchangers, and supporting systems can be monitored through updated operational states. Organizations should also improve Real-Time Industrial Data Intelligence by integrating sensor, SCADA, industrial IoT, equipment-health, energy-consumption, and process information within interoperable analytical environments. Greater attention should be given to data quality, time synchronization, sensor calibration, contextualization, and secure industrial communication because unreliable data can weaken both digital-twin accuracy and AI-supported decision-making. Predictive Maintenance Intelligence Capability should be integrated into routine asset-management practices through anomaly detection, fault diagnosis, degradation monitoring, remaining-useful-life assessment, and condition-based maintenance prioritization. Energy Optimization Intelligence Capability should similarly be incorporated into operational decision-making so that equipment loading, hydrogen production, storage use, process conditions, and energy consumption can be optimized jointly with asset-health requirements. Since EOIC and PMIC have produced the strongest regression effects, organizations should avoid treating maintenance and energy management as separate operational functions and should instead coordinate them through shared digital infrastructure and decision-support platforms. Managers should establish multidisciplinary teams involving maintenance engineers, process specialists, energy managers, automation professionals, AI developers, and digital-twin experts. Training programs should also be developed to improve technical understanding of hydrogen-system behavior, data analytics, physics-informed modeling, and cyber-physical integration. Finally, organizations should evaluate these capabilities through measurable performance indicators so that improvements in reliability, downtime reduction, energy efficiency, operational stability, and overall system performance can be tracked systematically.

LIMITATIONS

This study has several limitations that should be considered when interpreting its findings. First, the research has adopted a cross-sectional design, which has measured respondent perceptions within a single period and has therefore not captured changes in physics-informed AI maturity, digital-twin integration, maintenance performance, or energy optimization capability over time. Second, purposive sampling has been used because the research has required technically knowledgeable participants, but this approach has limited the statistical generalizability of the findings beyond the selected industrial contexts. Third, the study has relied on self-reported questionnaire data measured through a five-point Likert scale, meaning that the results have reflected professional perceptions rather than direct measurements from industrial sensors, maintenance databases, digital-twin platforms, or energy-management systems. Respondents may also have interpreted advanced technical concepts differently depending on their professional specialization and degree of exposure to hydrogen technologies. Fourth, the study has combined several hydrogen-related industrial environments, including production, storage, processing, power, chemical, and manufacturing contexts, although equipment configurations, operating conditions, technological maturity, and maintenance requirements may differ substantially across these sectors. Fifth, the dependent construct has integrated predictive maintenance and energy optimization performance into a common measure, which has supported the conceptual framework but may have reduced the visibility of differences between maintenance-specific and energy-specific outcomes. Sixth, the regression model has explained 73.2% of the variance in PMEOP, leaving a remaining proportion of performance variation associated with factors not included in the model, such as organizational culture, workforce competence, capital investment, cybersecurity, regulatory requirements, equipment age, and hydrogen-system design. Finally, the study has evaluated relationships among technological capabilities statistically but has not experimentally tested individual physics-informed algorithms, digital-twin models, or optimization techniques. These limitations have not invalidated the findings, but they have defined the empirical boundaries within which the results should be interpreted and applied.

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