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An information processing theory framework for intelligent fault diagnosis and predictive maintenance

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Introduction: Due to complex degradation processes and data-level, model-level, and system-level variations, industrial assets operate under high uncertainty. Existing PdM approaches still lack a unifying theoretical lens to align the uncertainty with technological and organizational capabilities. This paper aims to develop an IPT-grounded model, linking IPR and IPC for intelligent fault diagnosis and prescriptive maintenance.
Methods: The research design combines the elements of system-level technical benchmarking, organizational surveys, and case-based validation in a mixed-method approach. The methodology follows from operationalizing IPT constructs by mapping the sources of uncertainty, defining the dimensions of IPR, identifying mechanisms such as digital twins, multi-sensor fusion, federated/edge learning, multi-agent orchestration, and evaluating the "fit" between IPR-IPC using measurable indicators.
Results: The study develops a comprehensive multi-layer IPT framework comprising theoretical constructs, directional propositions, a translation layer converting the predictions to prescriptive maintenance actions, and an IPT Fit index for performance assessment. It also extends propositions on mechanism complementarity and provides scenario-based mechanism choice guidance under different archetypes of uncertainty.
Discussion and conclusion: It then shows how fit between IPR and IPC enhances diagnostic accuracy, lead time, decision quality, and operational performance. It introduces practical design rules: diagnose IPR prior to selecting mechanisms, design complementary modules, engineer translation workflows, and track the fit as a performance KPI. The research positions IPT as a core logic to drive the design of adaptive, explainable, operationally effective PdM systems, and one that provides explicit pathways for its empirical validation in future work.

KEYWORDS
information processing theory, predictive maintenance, digital twin, multi-sensor fusion, federated learning

1 Introduction

Electromechanical equipment and industrial assets such as turbines, circuit breakers, bearings, and injection machines function under intricate thermal, electrical, and mechanical stresses. These stressors, over a period of time, cause gradual deterioration through wear, fatigue, oxidation, or vibration irregularities. In turbo generators and other large-scale machines, shaft voltages and bearing currents increase insulation failure and bearing pitting risks to operational reliability and safety (Mailula and Saha, 2025a). Similarly, in high-voltage circuit breakers, increasing contact resistance indicates oxidation or erosion of contact surfaces, indicative of incipient faults that need real-time monitoring to avoid grid instability (Wang et al., 2025b). These instances demonstrate that the physical condition of industrial assets is dynamic and uncertain by nature. Monitoring of such degradation processes requires ongoing sensing, interpretation, and decision-support infrastructure instead of sporadic inspection cycles.

Classic maintenance paradigms either time-based or reactive are becoming less effective in the digitized industrial landscapes of today. They tend to cause excessive downtime, unnecessarily high maintenance expenses, and unexpected failures, mostly due to their reliance on fault-post diagnosis rather than predictive analytics (Mailula and Saha, 2025b; Martins et al., 2025). As a result, most industries are moving towards predictive and intelligent maintenance systems (PdM) that use sensors, big data platforms, and artificial intelligence (AI) to detect anomalies prior to catastrophic failure. The incorporation of machine learning (ML) and deep learning (DL) models in maintenance streams, particularly convolutional neural networks (CNNs), recurrent networks (RNNs), and ensemble structures has transformed condition monitoring by identifying fine signal variations and classifying initial faults with high accuracy (Costa et al., 2025; Eddai et al., 2025; Ovacıklı et al., 2025). Such algorithmic innovations form the cornerstone for self-diagnosing, adaptive maintenance environments.

Predictive maintenance has progressed, however, from the detection of faults to a decision-making discipline. More recent frameworks focus on explainable, prescriptive, and autonomous decision support in a closed-loop process that bridges data acquisition, fault detection, and action taken. Explainable predictive-maintenance architectures in railway systems offer interpretable warnings and causal interpretations that build operator trust and minimize diagnostic delay. In rotating-machine and compressor diagnostics, explainable deep models have minimized false alarms while guaranteeing fast corrective actions (Huang et al., 2023). Architecturally, digital twins (DTs) and edge computing have been significant enablers of this shift. By enabling virtual copies of physical systems that develop over time, DTs permit engineers to model hypothetical faults, forecast future performance, and configure prescriptive maintenance steps, while edge analytics reduce latency and bandwidth constraints (Xu et al., 2025).

The simultaneous emergence of federated learning and multi-agent systems further widens the paradigm. Federated architectures support decentralized model training across geographically distributed locations without centralizing sensitive information, thus enhancing model generalizability and adhering to data governance limitations (Kumar, 2025). Concurrently, autonomous AI agents and multi-agent orchestration systems handle diagnostic and scheduling tasks across distributed equipment networks as cognitive layers that orchestrate detection, prognosis, and resource allocation. Taken together, these advances herald a structural change: predictive maintenance is no longer an accessory technical feature but a core, knowledge-based function that combines sensing, analytics, and decision-making through industrial systems (Maican et al., 2025).

There remain, however, practical and theoretical issues. Heterogeneity, noise, and environmental uncertainty still cause ambiguity in model interpretation (Pan et al., 2025). Sensors can drift, degrade, or run asynchronously, generating errant data streams that test model resilience. Interference from the environment such as vibration, temperature, or electromagnetic noise also degrades signal quality (Martins et al., 2025). In addition, the “black-box” characteristic of most DL models restricts interpretability and transferability across domains (Zachariades and Xavier, 2025; Wang et al., 2025a). Operationally, high-frequency sensor networks produce voluminous amounts of data that are overwhelming for human operators and machine systems alike. Therefore, even if predictive accuracy is very high, conversion of predictions to economically and operationally feasible maintenance decisions is underdeveloped.

These constraints expose a fundamental conceptual fragmentation. Most intelligent maintenance research is technology-focused model optimization and precision, without a unifying theoretical framework for interpreting how information must be processed, combined, and responded to at technological and organizational levels. There is minimal direction on how to match the diagnostic task’s complexity and operational uncertainty with the technological solutions that aim to solve them. This gap requires a bridging theory able to describe not only what mechanisms do, but why and when they enhance performance.

Information Processing Theory (IPT) fills this gap. IPT conceptualizes organizations as information-processing systems that need to bridge information-processing requirements (IPR) created by uncertainty, task complexity, and interdependence with information-processing capacity (IPC) defined through available structures, technologies, and cognitive mechanisms. In intelligent maintenance systems, sensing networks, analytics models, and decision-support modules are expressions of IPC aimed at handling uncertainty and facilitating well-timed, accurate decisions. Deploying IPT helps answer three key questions in design: (1) Where does uncertainty stem from? (2) What information-processing tasks does it engender? and (3) What mechanisms are well-suited to accomplish these tasks?

Presenting predictive maintenance as an IPT issue therefore offers both diagnostic and prescriptive insight. It allows systematic mapping from uncertainty sources (sensor noise, interdependence) to information-processing mechanisms (DTs, edge AI, federated learning, multi-agent orchestration). By treating intelligent fault diagnosis as a multi-layered information-processing system, research transcends single-algorithmic advancements towards comprehensive, theory-based design principles for industrial decision support.

Drawing on this motivation, this research responds to three guiding research questions (RQs):

RQ1: How are maintenance-task characteristics, environmental conditions, and interdependence of components affecting the information-processing demands of intelligent maintenance systems?

RQ2: What technological and organizational processes increase information-processing capabilities to satisfy these needs under changing uncertainty conditions?

RQ3: How does alignment or fit between requirements and capacity for information processing impact diagnostic accuracy, operational reliability, and organizational decision quality?

The remainder of this paper is structured as follows: In Section 2, theoretical foundations are expounded and the logical relationship between uncertainty, information-processing needs, and mechanism design in intelligent maintenance ecosystems is established. Section 3 discusses the research methodology, outlining the sources of data, analytical design, and empirical methods undertaken for model development and validation. Section 4 presents the theoretical model which is An Information Processing Theory Framework for Intelligent Fault Diagnosis and Predictive Maintenance, defining major constructs, propositions, and relational mechanisms. Section 5 presents theoretical and practical implications of the proposed framework, noting its suitability for both academic development and industrial deployment. Lastly, Section 6 summarily concludes the paper by presenting the key findings, limitations, and future research directions.

2 Uncertainty, information processing needs, and mechanism design in intelligent mechanical maintenance systems

Mechanical maintenance systems function in environments of built-in uncertainty conditions influenced by intricate interactions of machinery, dynamic variations in operation, and varied sources of data. As industrial assets increasingly integrate through IoT and AI technologies, maintenance approaches must adapt to process massive, multidimensional streams of information and transform them into dependable decisions. From the view of Information Processing Theory (IPT), uncertainty is an intrinsic driver that raises the requirement for efficient information processing. For a resilience they can sustain, organizations and systems need to develop mechanisms that can learn to acquire, read, and respond to information effectively, scaling their processing capacity to their operating environment's complexity.

Recent research in deep learning, digital twins (DTs), multi-agent systems, IIoT architectures, and federated learning-based predictive maintenance (PdM) as a whole demonstrate that uncertainty does not merely degrade reliability, it drives architectural innovation. These mechanisms, algorithmic, digital, or organizational are specifically intended to cope with ambiguity, mitigate information asymmetry, and aggregate raw data into useful insights. Based on both technological and theoretical research (Mailula and Saha, 2025a; Huang et al., 2023; Gupta et al., 2025; Makkonen, 2021; Xu et al., 2025; Chen et al., 2025), the current section explains how uncertainty creates information-processing demands and how mechanism design in intelligent mechanical maintenance systems satisfies those demands.

2.1 Uncertainty in mechanical maintenance systems

Mechanical maintenance uncertainty is caused by several sources data-level anomalies, model-level fragility, and system-level interconnectedness. At the data level, machine decay is typically represented by noisy, missing, and non-stationary signals (Jin et al., 2025). Mailula K. O. and Saha A. (2025) illustrated this in big turbine generators, where shaft-earthing faults generate overlapping frequency bands obscuring fault signatures. Concomitantly, Huang et al. (2023) investigated air compressor systems with intricate correlations between temperature, flow rate, and pressure parameters, demonstrating that there can be flawed diagnostics in the absence of interpretable deep-learning models based on non-linear dependencies.

At the model level, uncertainty arises due to the restricted generalizability and interpretability of AI systems learned from restricted or domain-specific data sets (Esteban et al., 2025; Lee et al., 2025). Xu et al. (2025) discovered that predictive models for wind turbine gearbox gearboxes exposed to irregular wind forces, vibration fluctuations, and environmental changes tend to perform sub-optimally under diverse conditions. Likewise, Chen et al. (2025) emphasized that lubricant degradation data are affected by nonlinear and time-dependent interactions, requiring temporal decomposition and probabilistic reasoning to capture evolving degradation patterns.

Lastly, system-level uncertainty arises from decision hierarchies and interdependence among components. Mechanical breakdowns rarely occur in isolation; they cascade through coupled subsystems (Vlachou and Karakatsanis, 2025). Uncertainty in maintenance decisions can propagate across multiple components in a system when control, feedback, and integration mechanisms are insufficient, leading to cascading performance issues throughout the decision layers. This supports IPT's perception that environmental uncertainty fueled by task interdependence and complexity heightens the requirement for information-processing mechanisms with the ability to integrate data across boundaries.

Apart from technical uncertainties, organizational and strategic aspects also make maintenance decision-making more difficult. Makkonen (2021) emphasized that innovation adoption itself is an information-processing activity, where greater environmental uncertainty strengthens the demand for learning, feedback, and interpretive mechanisms that align analytical investments with strategic objectives. Collectively, these studies uncover uncertainty in maintenance systems ranging from sensor measurements to organizational decision-making and serve to confirm the necessity for adaptive, multi-layered processing structures.

2.2 Information-processing needs emerging from uncertainty

With increasing uncertainty, the information-processing demands of maintenance systems increase along three mutually related dimensions: sensing and data acquisition, interpretation and prediction, and decision coordination and transparency.

2.2.1 Sensing and data acquisition needs

Industrial systems generate huge amounts of multi-sensor data that collects vibration, temperature, torque, and pressure with each having different scales and noise properties. Conventional threshold-based techniques are not suited to detect normal operating variability and early warning signs of faults. Xu et al. (2025) solved this problem by incorporating multi-source data fusion into a digital twin-based architecture for wind turbine gearboxes. By comparing physical sensor data with simulated digital counterparts, the system processed differences between them as early warning signs of faults. This solution demonstrates IPT's principle of aligning environmental complexity with more sophisticated sensing and contextual integration.

Gupta et al. (2025) further developed this concept through an information system powered by IIoT that gathers and orchestrates heterogeneous streams of shop-floor devices, middleware, and enterprise analytics. Their case study demonstrated that distributed sensing and cloud integration significantly enhance situational awareness and reduce decision latency parameters that are crucial for systems experiencing constant uncertainty in data arrival and machine state changes.

2.2.2 Interpretation and predictive needs

After raw data are gathered, the problem is to convert uncertainty into predictive knowledge. Chen et al. (2025) developed a multi-sensor fusion mechanism based on deep learning (SFTI-LVAE), which separates signals into trend, seasonal, and residual parts. The structure improves interpretability by making it apparent how thermal, chemical, and tribological conditions lead to lubricant degradation. Likewise, Huang et al. (2023) and Nguyen et al. (2025) created an explainable deep-learning model for air compressor monitoring that allowed human operators to track fault causes by following feature-level explanations. Such mechanisms meet IPT's need for adaptive learning and interpretive transparency, connecting raw data and decision confidence (Lamsaf et al., 2025).

Xu et al. (2025) utilized an optimization-augmented temporal convolutional network with attention modules to make gearbox fault predictions. With the addition of a Whale Optimization Algorithm (WOA), their model dynamically adjusted parameters to mitigate non-stationary environments, in keeping with IPT's concept that firms need to increase their computational resources in line with uncertainty volatility.

2.2.3 Decision coordination and transparency needs

At broader organizational levels, uncertainty becomes coordination complexity, which make the necessity to coordinate information flows at hierarchical decision layers. Multi-agent architectures for predictive maintenance structure specialized agents to handle discrete information-processing tasks. The diagnostic agent is responsible for sensor fusion and anomaly detection; the scheduling agent determines the timing and allocation of maintenance resources; and the digital twin agent models' operational conditions. This breakdown reflects IPT's distributed processing framework, whereby specialist subsystems cooperate to minimize uncertainty via systematic information exchange.

Makkonen (2021) also highlighted the importance of cross-functional dialogue and interpretive systems within organizations, demonstrating that decision support effectiveness is reliant on cognitive and structural processes such as feedback loops, communication networks, and interpretive alignment that translate analytical output into shared understanding.

2.3 Mechanism design for managing uncertainty

In order to deal with the varied information-processing needs arising out of uncertainty, organizations develop technological and structural mechanisms that stretch their processing abilities. Such mechanisms are adaptive architectures that contain IPT's fit principle matching the system's information-processing ability to environmental uncertainty.

2.3.1 Digital twin–based mechanisms

Digital twins are one of the strongest uncertainty-resolution mechanisms. Li H et al. (2025) and Xu et al. (2025) illustrated how DTs are virtual laboratories, facilitating real-time synchronization between physical systems and digital counterparts. Through the simulation of hypothetical operating scenarios, DTs transform unstructured uncertainty into structured diagnostic knowledge (Fadel and Alelaj, 2025). Edge-AI–enabled digital twin architectures allow local nodes to perform fast anomaly detection while cloud-based twins handle complex simulations and optimizations. This hierarchical structure aligns information-processing depth with uncertainty intensity, enabling rapid local responses to short-term anomalies and strategic insights for long-term decision-making.

2.3.2 Multi-sensor fusion and deep learning mechanisms

Deep-learning architectures like Chen et al. (2025), Huang et al. (2023) and Makwane et al. (2025) increase information-processing capability by feature extraction and fusion. These models capture correlations between sensor modalities, facilitating adaptive diagnosis even in noisy, multi-source scenarios (Gęca et al., 2025; Vlachou et al., 2025). In IPT terms, these mechanisms improve the system's processing richness, allowing it to process equivocal information via multi-layer representation learning and probabilistic reasoning.

2.3.3 Federated learning mechanisms

Kumar (2025) proposed federated learning as a distributed framework for dealing with data heterogeneity and uncertainty of privacy. By training models on decentralized nodes without exchanging sensitive information, FL provides global generalization while being respectful of local context. This arrangement is in line with IPT's evolution from intra-organizational to inter-organizational networks of information processing where various actors work together in handling uncertainty while being autonomous.

2.3.4 IIoT information system architecture

Gupta et al. (2025) emphasized that IIoT structures are organizational information-processing systems that combine real-time data collection with enterprise-grade analytics. Through decentralized decision-making and edge computing, IIoT systems reduce latency and improve contextual responsiveness and hence minimize information overload and facilitate predictive coordination in distributed operations.

2.3.5 Organizational and strategic mechanisms

Although technology pushes the mechanical and analytical limits of maintenance systems, organizational processes enforce interpretability and decision congruence. Cross-functional communication and interpretative processes were singled out by Makkonen (2021) as critical to successful innovation amid uncertainty, while connected strategic posture to taking on analytical tools. These findings emphasize that both cognitive and structural congruence are needed for efficient uncertainty management where technology architectures must be reinforced by organizational routines that facilitate shared sense-making, feedback, and responsiveness.

2.3.6 Organizational information-processing mechanisms as equal determinants of IPC

While technological architectures expand computational IPC, organizational capacity is equally critical in enabling effective information processing. Governance structures define decision rights, data stewardship, and risk accountability; skill maturity and interpretive proficiency determine how predictive insights are translated into operational meaning; and CMMS/ERP integration ensures that analytical outputs cascade into timely, implementable actions. Organizational information-processing mechanisms are, thus, not complementary add-ons but co-equal determinants of IPC, which moderate the realization of technical capability into operational performance. This is consistent with IPT's foundational stance that information processing is jointly socio-technical rather than solely model-driven.

2.4 Integrating the IPT lens: from uncertainty to mechanism design

Throughout the reviewed researches, a recurring causal sequence is found, connecting uncertainty, information-processing requirements, and mechanism design. Uncertainty in intelligent maintenance systems originates from various aspects, such as sensor noise, heterogeneity of multi-source data, model vagueness, and environmental uncertainty, all of which enhance the complexity and amount of information to be processed. These uncertainties give rise to particular information-processing requirements, including real-time sensing to enable timely anomaly detection, contextual data fusion to provide complete situational awareness, interpretive modeling to obtain diagnostic meaning, and decision coordination to map analytical insights onto operational responses. To meet these requirements, mechanism design matures through a complementary set of organizational and technological solutions where digital twins allow for simulation-based reasoning and predictive insight; multi-sensor fusion creates enhanced contextual awareness and diagnostic precision; Industrial Internet of Things (IIoT) architectures facilitate effortless data integration between assets; AI agents enable autonomous decision orchestration; federated learning provides distributed model collaboration without data loss; and organizational learning systems ensure continuous adaptation and strategic alignment. Together, this sequence—Uncertainty → Information-Processing Need → Mechanism Design—is the core information-processing alignment logic that underlies smart fault diagnosis and predictive maintenance in cyber-physical systems.

This triadic evolution encases IPT in smart mechanical maintenance. With rising uncertainty, the system widens its scope of information processing by embracing more profound analytics, wider integration, and larger autonomy. Thus, smart maintenance systems become distributed, adaptive ecosystems that reflect organizational cognition: sensing, reasoning, learning, and deciding in real time.

Ultimately, uncertainty is not an issue to be minimized; it is a motive for architectural complexity. By leveraging stacked mechanisms such as digital twins, edge computing, multi-agent systems, federated learning, and IIoT integration, industrial maintenance systems translate uncertainty into formalized knowledge. Informed by IPT, this innovation represents a move from reactive maintenance to a smart, theory-based model of predictive and prescriptive reliability management.

Despite significant advancement in PdM mechanisms, existing literature remains largely mechanism-centric, lacking a theory-based contingency logic that guides when a particular mechanism should be used relative to the type of uncertainty present. There is limited research connecting uncertainty-driven information-processing needs with mechanism selection and almost no work treating translation and organizational adaptation as core determinants of outcome effectiveness (Said et al., 2025). Furthermore, current literature provides insufficient theoretical linkage between technical outcomes (accuracy, lead time) and organizational outcomes (decision quality, downtime reduction). The proposed IPT framework directly addresses these gaps by explicitly linking uncertainty → IPR → IPC → FIT and by defining translation as a core organizational pipeline required for value realization.

2.5 Mechanistic causality justification of the IPT chain

Theoretically, the directionality of the relationships proposed here is grounded in IPT logic: Uncertainty → IPR → IPC → Fit → Outcomes, and is also supported by the empirical findings of prior studies. According to IPT, environmental uncertainty increases the volume, variety, and equivocality of information to be processed, thereby increasing the information-processing requirements of the organization (Tushman and Nadler, 1978; Makkonen, 2021). In the context of intelligent mechanical maintenance, uncertainty due to sensor noise, structural interdependence, and variability in the task at hand similarly increases the diagnostic task's level of complexity, therefore increasing IPR (Chen et al., 2025; Xu et al., 2025).

Mechanisms such as Digital Twins, multi-sensor fusion, federated/edge learning architectures, and agentic orchestration increase IPC by expanding sensing resolution, enhancing interpretive richness, reducing communication bottlenecks, and improving decision coordination (Gupta et al., 2025). When IPC matches the IPR induced by uncertainty, diagnostic accuracy, predictive lead times, downtime reduction, and decision quality improve—thereby demonstrating the performance effect of "fit." Prior maintenance studies have also shown that even highly accurate

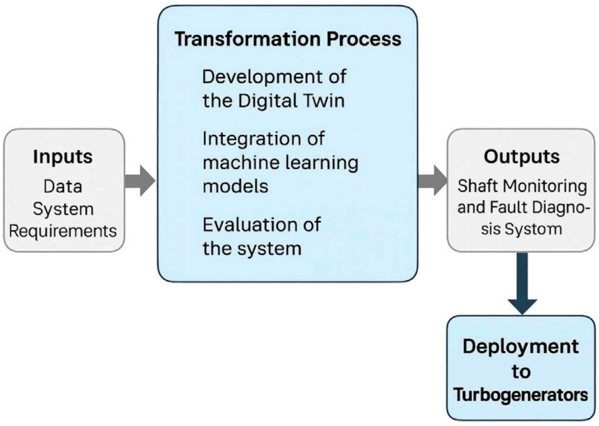

FIGURE 1
Methodological framework based on the adapted information processing theory (Tushman and Nadler, 1978).

models do not translate to organizational performance when translation and IPC alignment is weak.

Therefore, the causal pathway here is not only theoretical but also mechanistically justified: uncertainty creates IPR; mechanisms enhance IPC; and the alignment of the two, or the fit, is the condition that will lead to both technical and organizational outcomes. This mechanistic justification also reinforces the internal theoretical validity of the framework before the testing in the empirical Section 3.

3 Methodology

This research employs a multi-method research approach combining technical experimentation, organizational survey, and case-based validation to empirically validate the conceived Information Processing Theory (IPT) framework for intelligent fault diagnosis and predictive maintenance (PdM). The methodological goal is two-pronged:

a. to assess how uncertainty from mechanical systems maps into information-processing requirements, and
b. to analyze how various information-processing capabilities like multi-sensor fusion, digital twins, edge/federated learning, and AI-agent orchestration impact diagnostic performance and organizational decision results.

The research design reflects IPT's central contention that organizational effectiveness is contingent on the alignment of an organization's information-processing requirements with its information-processing capacity. To that end, this study uses a multi-method approach of controlled system-level experiments (to measure detection and prognostic accuracy), field case studies (to examine mechanism adoption and alignment), and cross-organizational surveys (to gauge IPT constructs and organizational performance).

Figure 1 depicts the conceptual framework modified from Tushman and Nadler's (1978) Information Processing Theory. It visualizes the sequence from environmental and task uncertainty to information-processing needs to mechanism design and organizational consequences. As indicated, uncertainty arising from machine complexity, heterogeneity of data, and interdependence of the task gives rise to the necessity for stronger sensing, integrating, and interpreting mechanisms. These needs are fulfilled through technological and organizational means like digital twins, multi-sensor fusion, federated learning, and AI-agent decision coordination. The resultant "fit" between capacity and processing needs results in better maintenance performance, decision quality, and organizational reliability.

The model illustrates the methodological flow connecting environmental and task uncertainty, information-processing requirements, and technological and organizational mechanisms. Sustaining a dynamic fit among processing requirements and capacity strengthens predictive maintenance effectiveness and decision results.

The technical aspect utilizes instrumented tools and surrogate data sets to assess detection and prediction capabilities at different uncertainty levels. Extending previous technical structures (Mailula and Saha, 2025b; Xu et al., 2025; Chen et al., 2025), the experiments compare baseline detection models like CNN, LSTM, and transformer hybrids (Fan et al., 2025) with advanced IPT-aligned structures:

1. Multi-sensor fusion models (SFTI-LVAE type) for contextual integration (Chen et al., 2025).
2. Digital twin–augmented inference, where simulated counterfactuals are employed to resolve signal ambiguity (Li X et al., 2025; Xu et al., 2025).
3. Federated learning deployments for decentralized model generalization across sites (Sekar et al. (2025).
4. Agentic orchestration modules that transform diagnostic output into scheduling decisions (Sekar et al., 2025).

Experimental hardware consists of rotating equipment, compressor test benches, and induction motor test rigs. Where hardware on-site is not feasible, publicly available or partner-supplied datasets (e.g., bearing and compressor datasets in Eddai et al., 2025; Mailula and Saha, 2025a) are used for reproducibility.

In order to systematically operationalize uncertainty, experiments control three forms of uncertainty based on the IPT conceptualization:

a. Data-level uncertainty through additive noise, missing channels, and sensor drift;
b. Uncertainty at the model level through domain shifts and limited labeled data; and
c. Uncertainty at the system level through interactive faults and concurrent component degradation.

For every condition, the metrics of evaluation are detection accuracy, precision, recall, F1-score, time-to-detection, false alarm rate, and prognostic horizon (lead time). System-level operational metrics like computational latency, bandwidth usage, and edge inference duration are recorded to evaluate trade-offs in distributed deployments (Gupta et al., 2025).

The organizational construct examines the IPT relationships depicted in Figure 1: environmental/task uncertainty → information-processing requirements → information-processing capacity (mechanisms) → organizational effectiveness (fit and outcomes). In line with previous IPT and technology-adoption research (Makkonen, 2021), a systematic survey instrument will be created and completed by maintenance managers, reliability engineers, and operations supervisors. Survey constructs will include perceived uncertainty (sensor unreliability, operational variability), processing requirements (need for real-time analysis, interpretability, coordination), mechanism deployment (use of digital twins, multi-sensor fusion, federated/edge AI, AI agents), and organizational outcomes (decision quality, downtime reduction, trust in analytics). Survey items will be adapted and validated from established empirical works (Gupta et al., 2025; Sekar et al., 2025).

To enhance quantitative results, there will be several case studies with three to five industry partners in energy, rail, and manufacturing industries. Cases will be chosen to cover contrasting uncertainty profiles and PdM maturity levels. Data will be gathered through semi-structured interviews, architecture descriptions, system logs (where available), and observation of decision-making processes. Case analysis will bring out real-world limitations such as explainability rules, legacy integration, and human-in-the-loop workflows that affect IPT fit (Shaban et al., 2025).

Analytically, the research has a two-track approach.

At the system level, outcomes will be assessed using cross-validation, paired statistical testing, and ablation analysis to separate mechanism effects (e.g., performance gain due to DT enhancement).

At the organizational level, survey data will be examined using structural equation modeling (SEM) to test IPT-derived hypotheses:

- Greater perceived uncertainty results in increased processing demands.
- Increased information-processing capability (via mechanism uptake) moderates the uncertainty outcome association.
- Fit (capacity and requirements alignment) moderates effects on downtime reduction and decision quality.

A multilevel model will connect system-level measures of performance (e.g., detection accuracy) to organizational survey items to test if technical reliability is translated into higher decision quality.

Reliability and validity processes involve survey pre-testing, internal consistency testing (Cronbach's $\alpha > 0.7$), confirmatory factor analysis, and triangulation between experiments, surveys, and cases. Technical reproducibility is guaranteed through open disclosure of code, hyperparameters, and data where allowed. Ethical adherence will be ensured through institutional review, anonymization of working logs, and federated-learning solutions for privacy-sensitive partnerships (Kumar, 2025).

In short, this approach implements IPT's core idea of fit between information-processing need and ability on the basis of a systematic mixed-method design. Through experimental quantification of mechanism performance coupled with organizational-level assessment of processing alignment and success, this research hopes to yield both theoretical confirmation and practical advice for IPT-congruent predictive maintenance architectures.

3.1 Illustrative application example

To make it concrete, suppose the IPT framework is applied to a wind turbine gearbox predictive maintenance problem. With high structural interdependence, high model uncertainty, and increased IPR comes the need for counterfactual simulation and resolution of temporal variances along the chain. Digital Twins, in this case, would be the superior IPC mechanism due to its capability to model dynamic internal state evolution and alternative degradation trajectories compared to pure fusion or basic federated learning mechanisms. Under an alternative scenario where the turbines are geographically dispersed and bandwidth constraints exist, then the mechanism of Federated Learning becomes superior owing to restrictions in communication and privacy. The foregoing example shows that IPT reasoning supports evidence-based mechanism selection rather than intuitive mechanism preference; hence, this proposed causal chain is operationally usable in real industrial PdM contexts.

As this paper is a theory-development contribution, statistical analysis is not conducted at this stage. Statistical calibration and empirical testing of the IPT Fit construct will be conducted in future empirical validation studies.

4 Theoretical model—an information processing theory framework for intelligent fault diagnosis and predictive maintenance

4.1 Introduction to the theoretical model

This section formulates a domain-specific Information Processing Theory (IPT) model of intelligent fault diagnosis and predictive maintenance (PdM). The model operationalizes IPT's key observation that organizational performance rests on matching information-processing demand with information-processing ability into tangible constructs and mechanisms specific to mechanical maintenance systems. Founded solely on the literature amassed earlier in this manuscript (e.g., Mailula and Saha, 2025a; Chen et al., 2025; Kumar, 2025; Xu et al., 2025), the model prescribes (a) the antecedent sources of information-processing demand (task characteristics, environment, interdependence), (b) the forms of information-processing requirements (IPRs) they create, (c) the technological and organizational mechanisms that provide information-processing capacity (IPC), (d) the translation layer that translates prediction into action, and (e) the alignment between requirements and capacity as the key determinant of technical and organizational outcomes. The framework is designed to inform empirical testing (Section 3) as well as act as a prescriptive design map for PdM architecture decisions.

4.2 Constructs and operational definitions

4.2.1 Maintenance task characteristics (MTC)

Maintenance Task Characteristics are inherent attributes of a maintenance or monitoring task that create information demand. Important dimensions are complexity (single vs. multi-fault; multiple signal demands), temporal urgency (mandatory prognostic window, time-to-detection), criticality (safety or production effect), and monitoring rate. Operating indicators are sensors per asset number, fault class cardinality, prognostic lead time, and safety-criticality rating. Literature illustrations: high-frequency bearing and shaft condition monitoring (Mailula and Saha, 2025a; Eddai et al., 2025) and wind-gearbox prognostics with long horizons and multi-source integration (Xu et al., 2025).

4.2.2 Maintenance task environment (MTE)

Maintenance Task Environment refers to the outside world that influences information availability and noise, such as physical environments (temperature, vibration), network limitations (bandwidth/latency), regulatory requirements (explainability), and heterogeneity in legacy. Measurements encompass ranges of environmental variability, observed network latency/bandwidth, and existence/strength of explainability or certification needs. For instance, severe turbine environments and EMI-dense converter stations create non-stationarity and corruption of signals (Xu et al., 2025; Martins et al., 2025).

4.2.3 Maintenance task interdependence (MTI)

Task interdependence conveys the extent to which component states and maintenance decisions interact across systems such as serial/parallel failure propagation, spares sharing, and scheduling conflicts. Indicators are count of coupled subsystems, spare-parts sharing indices, and failure-propagation risk scores. Highly interdependent situations are grid assets and multi-shaft drivetrains where local faults cascade to system-level failure (Li and Li, 2025).

4.2.4 Information-processing requirements (IPR)

IPRs are the specific information work required by uncertainty and characterized by the antecedent constructs: sensing resolution and synchronisation, breadth and heterogeneity of fusion, temporal timeliness (tolerances for latency), interpretability, and coordination needs. IPRs instantiate what the PdM system needs to do (e.g., streaming temporal modelling, multi-modal fusion, uncertainty quantification). Examples: lubricant health monitoring needs trend decomposition and probabilistic health indices (Chen et al., 2025); compressor monitoring needs noise-robust anomaly detection and explainability (Huang et al., 2023).

4.2.5 Mechanisms for enhancing information-processing capacity (IPC)

Mechanisms are the structural and technological instruments that increase IPC. Four families predominate the literature and the model under proposal:

1. Multi-sensor fusion and DL advanced (SFTI-LVAE, TCN, CNN–transformer hybrids) — for contextual integration and robust feature learning (Chen et al., 2025; Fan et al., 2025).
2. Digital Twins (DTs) — for counterfactual simulation and structural uncertainty resolution (Xu et al., 2025; Li and Li, 2025).
3. Edge/Federated Learning and TinyML—for managing latency, privacy, and decentralized generalization (Gupta et al., 2025; Kumar, 2025).
4. AI-agent/Multi-agent orchestration—for breaking down cognitive tasks (diagnosis, scheduling) and closing the loop from prediction to action (Sekar et al., 2025).

4.2.6 Maintenance capabilities/information-processing capacity (IPC)

IPC is the actual ability of a system to satisfy IPRs and consists of technical resources (model ensembles, DT fidelity, edge compute) and organizational assets (capabilities, documented workflows, governance). Metrics comprise ensemble diversity, DT simulation fidelity scores, edge latency benchmarks, staff expertise indices, and availability of formal decision workflows. Empirical research indicates that IIoT architectures combining shop-floor and enterprise analytics substantively boost IPC for real-time decisions (Gupta et al., 2025).

4.2.7 Integration and decision-support (translation layer)

The translation layer maps predictive outputs to prescriptive, actionable steps: scheduling, spare provisioning, safety inspections. Metrics are decision latency, prescriptive accuracy (% actions that led to resolution), human-in-the-loop intervention rate, and scheduler optimization gain. Included in this layer are mapping modules (diagnosis→risk score→policy), CMMS/ERP integration, dashboards, and operator interfaces. The literature emphasizes that even robust detection models need good translation in order to affect downtime metrics (IIoT case studies; power-plant reviews).

4.2.8 IPT fit and outcomes

Fit refers to alignment between IPR (requirements) and IPC (capacity). Fit is measured as a gap index (required capacity minus provided capacity) and as a KPI for evaluation. Outcomes encompass diagnostic performance (accuracy, precision, F1, lead time), operational performance (reduction of downtime, MTBF improvements), and organizational measures (quality of decision, trust). The literature cites robust results where fit is good (e.g., DT + fusion in wind gearbox prognostics) and chronic failures of operationalization where fit is poor (evaluated power-plant studies).

Tables 1–3 together show the empirical and conceptual basis for each IPT construct within predictive-maintenance applications.

The synthesis establishes that fit—alignment of information-processing requirements (IPR) with information-processing capacity (IPC)—repeatedly produces better maintenance results, operational reliability, and decision quality across categories.

4.2.9 Comparative fit analysis across information-processing mechanisms

While Table 1 provided descriptive mapping of mechanisms to IPT constructs, a comparative analysis is needed to shed light on which mechanisms deliver superior IPC under different uncertainty categories. Following IPT contingency logic, no mechanism is

TABLE 1 Mapping of information processing theory constructs—electro-mechanical and manufacturing maintenance tasks (2022–2025).

References	Maintenance task characteristics	Maintenance task environment	Maintenance task interdependence	Information-processing requirements (IPR)	Mechanisms for improving information-processing capacity	Maintenance capabilities (IPC)	Integration and decision-support (translation layer)	IPT fit and outcomes
Mailula and Saha (2025a)	High-frequency, multi-signal monitoring of shaft/bearing faults	Harsh electrical–thermal EMI environment	Electrical faults cascade to insulation failures	Multi-domain sensing; early-warning analytics	Multi-sensor arrays; ML classification	Electrical/vibration instrumentation	Real-time alarms → protection systems	Strong fit → early detection
Mailula and Saha (2025b)	Transient brush-fault detection; fine time resolution	EMI-rich generator halls	Brush faults affect bearings and grounding	Temporal decomposition; interpretability	DL with denoising and attention	Labelled data pipelines	Risk-score dashboards	Fit reduces false positives
Wang et al. (2025b)	Real-time contact-resistance monitoring	High-voltage switchgear	Breaker health → grid reliability	Multi-sensor fusion and temp compensation	RF-AdaBoost fusion	Calibrated acquisition units	Health indices → control centers	Accurate state awareness
Kabashkin (2025)	Acoustic fault detection for rotating parts	Offshore turbines; ambient noise	Acoustic ↔ vibration features	Low-latency acoustic analysis	FFT/STFT + CNN.	Embedded acoustic nodes	Acoustic alerts → dashboards	Fit reduces inspection cost
Pan et al. (2025)	Subtle acoustic anomalies; safety-critical	HV converter stations	Valve faults → grid stability	Noise-robust unsupervised learning	Feature-aware VAE.	Acoustic sensing + unsupervised AI.	Alarms → human verification	Fit = early risk mitigation
Costa et al. (2025)	Multi-signal machine monitoring	Factory lines; variable duty	Fault ↔ process throughput	Real-time classification	Supervised ML + feature engineering	Integrated sensors	Fault alerts → scheduler	Fit reduces downtime
Eddai et al. (2025)	High-freq vibration analysis	Industrial noise; load variation	Bearing → shaft damage	High-res features; domain robustness	TF analysis + ensemble ML.	Vibration networks	Fault labels → maintenance	Fit improves reliability
Zachariades and Xavier (2025)	Multi-modal diagnostics	Varied machine types	Strong subsystem interdependence	Cross-modal fusion; uncertainty	Hybrid physics + AI.	Diagnostic toolchains	Multi-layer dashboards	Fit = trust and accuracy
Wang et al. (2025b)	Multi-sensor spring mechanism	Electrical substations	Spring ↔ actuation	Real-time fusion and interpretability	RF-AdaBoost ensemble	Fusion hardware	Diagnostics → planning	Fit ↑ speed and reliability
Martins et al. (2025)	Non-invasive acoustic screening	Remote turbines	Audio ↔ vibration link	Edge processing; fast inference	TinyML + spectrogram CNN.	Remote acoustic nodes	Warnings → inspection	Fit cuts costs

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TABLE 2 Mapping of IPT constructs—energy, transport and environmental maintenance tasks (2022–2025).

References	Maintenance task characteristics	Maintenance task environment	Maintenance task interdependence	Information-processing requirements (IPR)	Mechanisms for improving information-processing capacity	Maintenance capabilities (IPC)	Integration and decision-support (translation layer)	IPT fit and outcomes
Xu et al. (2025)	Multi-sensor gearbox monitoring	Remote farms	High drivetrain link	Multi-source sync	DT + TCN fusion	Edge detection	DT → maintenance window	Fit ↑ accuracy
Fan et al. (2025)	Spectral time-series faults	Industrial plants	Moderate	Cross-modal fusion	CNN + transformer	Deep ensembles	Dashboards → operators	Fit ↑ trust
Priya et al. (2025)	Real-time UAV engine monitoring	Mobile aero systems	High	Ultra-low latency	SVD LSTM.	Edge compute	Risk → autopilot alerts	Fit ↑ safety
Kokare et al. (2025)	SoH and capacity fade	EV fleets	High	Uncertainty quantification	Hybrid physics + ML.	Edge BMS.	BMS → scheduling	Fit reduces degradation
Bougoffa et al. (2025)	Multi-modal solar faults	Outdoor PV.	Moderate	Domain generalization	Hybrid DL + physics	Cloud updates	Fault maps → crew	Fit ↑ localization
Pratticò et al. (2025)	Thermal QC of devices	Labs/production	Low	Spatial feature extraction	FEM + CNN.	Simulation augmentation	Thermogram → QC.	Fit ↓ rework
Sheka and Saraswathi (2025)	Networked components	Assembly systems	High	Relational fusion	GNN + attention	Topology monitoring	Priority alerts	Fit ↑ root-cause clarity
Sekar et al. (2025)	Heterogeneous assets	Mixed factory	Moderate–high	Data harmonization	IIoT middleware + ML.	Shop-floor integration	CMMS work orders	Fit ↑ MTTR.
Ūselis et al. (2025)	High-speed multi-sensor	Noisy rail vehicle	High	Real-time anomaly detection	DL fusion + edge	Onboard inference	Alerts → ops center	Fit ↑ safety
Thango (2025)	Harmonic signature detection	HV substation	Moderate	Time-freq analysis	DWT + SVM.	Lightweight DSP.	SCADA integration	Fit ↑ reliability
Wang et al. (2025a)	SCADA data analysis	Remote turbines	High	Feature selection; trend tracking	AE ensemble + FMSA.	Edge/cloud fusion	Anomaly → schedule	Fit ↑ early detection
Bunyan et al. (2025)	Thermal fault classification	High-temp zones	Interdependent zones	Explainability	XGBoost + FI.	Thermal sensors	Alarms → tickets	Fit ↑ accuracy
Rao et al. (2025)	Many low-power sensors	Harsh industry	Shared network	Low-latency fusion	Edge DTree + CNN-LSTM.	Edge nodes	Edge + cloud alerts	Fit ↓ latency
Arciniegas et al. (2025)	Fast vibration detection	Noisy shop-floor	Low	Real-time FFT on MCU.	TinyML pipeline	Edge MCU.	MQTT dashboards	Fit ↑ speed

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TABLE 2 (*Continued*) Mapping of IPT constructs—energy, transport and environmental maintenance tasks (2022–2025).

References	Maintenance task characteristics	Maintenance task environment	Maintenance task interdependence	Information-processing requirements (IPR)	Mechanisms for improving information-processing capacity	Maintenance capabilities (IPC)	Integration and decision-support (translation layer)	IPT fit and outcomes
Sikinyi et al. (2025)	Cross-machine bearing faults	Load shift environments	Moderate	Domain generalization	KA-Conv + transformer	Ensemble models	Fault class + confidence	Fit ↑ accuracy
Tan and Carroll (2025)	SCADA pipeline design	Offshore turbines	High	Pipeline interpretability	LLM guidance	Human-in-loop design	Validated deployment	Fit ↑ development speed
Spandonidis et al. (2025)	Continuous KPI forecasting	Maritime context	High	Temporal fusion	ANN + DT.	Shipboard DTs	KPI → prescriptive action	Fit ↑ efficiency
Shaban et al. (2025)	Multi-objective monitoring	Building indoor	Zone interdependence	Multi-sensor fusion	IoT + cloud AI.	IT/OT integration	IAQ → energy optim	Fit conceptual
Lim et al. (2025)	RUL forecasting	Marine engines	Cylinder linkages	Time-series forecast	ML regression	Engine data pipeline	RUL → port schedule	Fit ↑ planning
Li H et al. (2025)	Rotor multi-signal diagnostics	Power plants	Bearing–shaft link	Multi-modal fusion	Hybrid AI models	Smart diagnostics	Actionable insights	Fit ↑ system reliability

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TABLE 3 Mapping of information processing theory constructs—cross-domain, IoT, and organizational studies (2022–2025).

References	Maintenance task characteristics	Maintenance task environment	Maintenance task interdependence	Information-processing requirements (IPR)	Mechanisms for improving information-processing capacity	Maintenance capabilities (IPC)	Integration and decision-support (translation layer)	IPT fit and outcomes
Bonacina et al. (2025)	Multi-fault bearing tests; benchmark dataset.	Lab tracks; controlled but noisy	Cross-cart interaction high	Synchronization and feature selection	Shared benchmark fusion pipeline	Dataset supports ML development	Benchmark → model comparison tool	Fit facilitates cross-study evaluation
Adekunle et al. (2025)	Multi-class gas-analysis faults	Substation field testing	System-level impact high	Gas-ratio feature selection; class imbalance	Ensemble RF/XGBoost/ LightGBM.	Historical datasets (>0.99 accuracy)	Diagnostic labels → asset plans	Fit reduces catastrophic failures
Chen et al. (2025)	Continuous lubricant health indexing	Engine tribological systems	High (gears ↔ bearings)	Trend decomposition; forecasting	LVAE fusion pipeline	Multi-sensor arrays; explainability modules	Health index → graded actions	Fit = zero false alarms (~6 h lead)
Quiles-Cucarella et al. (2025)	Multi-fault PV classification	Outdoor fields; variable irradiance	Moderate	Adaptive classifier selection	Bagged trees + NN hybrid	Large datasets	Mode-aware alerts → crew	Fit ↑ accuracy and O&M savings
Primawati et al. (2025)	Legacy equipment; multi-class bearings	Workshop noise	Moderate	Small-sample explainable learning	Random forest + fuzzy logic	Low-cost sensing (~94% accuracy)	Alerts → operator dashboard	Fit ↑ availability of old assets
Li X et al. (2025)	Oil degradation monitoring	Steel mills; high load fluctuations	High coupling (gearbox ↔ rollers)	Real-time viscosity data fusion	IoT + DL predictive model	Sensor retrofits on legacy plants	Cloud alerts → maintenance portal	Fit reduces unplanned shutdowns
Sekar et al. (2025)	Multi-equipment real-time monitoring	Smart factory (heterogeneous data)	High network interdependence	Interoperability + stream analytics	MQTT + edge DL + cloud broker	IT/OT bridge middleware	Dashboards + CMMS integration	Fit improves OEE and throughput
Ūselis et al. (2025)	Distributed sensors; latency-sensitive	Edge computing nodes	Moderate inter-node dependency	Latency vs. accuracy trade-off	Federated learning + edge AI.	Edge nodes with adaptive capacity	Aggregated dashboards	Fit ↑ responsiveness and privacy
Sekar et al. (2025)	Secure sensor traceability	Multi-organization maintenance	High inter-firm dependency	Trust + immutability requirements	Blockchain + IPFS + smart contracts	Distributed ledger capability	Shared data across ecosystem	Fit ↑ data integrity and coordination
Xu et al. (2025)	Cross-plant model training	Distributed enterprises	High collaboration interdependence	Privacy-preserving learning	FL aggregation + personalization	Edge ML capacity per plant	Federated model updates	Fit ↑ accuracy without data sharing
Xu et al. (2025)	DT design assessment framework	Cross-industry	Moderate	DT readiness evaluation	Hierarchical scoring model	DT assessment tool kits	Adoption roadmap	Fit guides DT investment
Gupta et al. (2025)	Strategic transition tasks	Multi-level organization	High task interdependence	Integration of IT and OT knowledge	Capability maturity models	Human–machine collaboration	Governance dashboards	Fit ↑ digital transformation success

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TABLE 3 (*Continued*) Mapping of information processing theory constructs—cross-domain, IoT, and organizational studies (2022–2025).

References	Maintenance task characteristics	Maintenance task environment	Maintenance task interdependence	Information-processing requirements (IPR)	Mechanisms for improving information-processing capacity	Maintenance capabilities (IPC)	Integration and decision-support (translation layer)	IPT fit and outcomes
Gupta et al. (2025)	Complex decision co-ordination	Smart manufacturing plants	High	Dynamic information fit modeling	AI decision support + simulation	Hybrid decision layer	Automated recommendations	Fit ↑ decision accuracy and speed
Makkonen (2021)	Theoretical cross-framework study	Conceptual/review	Broad organizational scope	Fit vs. adaptation theory	Conceptual mapping approach	N/A	Integration of org and tech factors	Fit explains PdM maturity
Rajaperumal and Columbus (2024)	Conceptual integration of IPT constructs	Multi-sector	Variable	Uncertainty vs. capacity analysis	Framework derivation	Research guideline	Academic framework linkage	Fit enables model validation
Barnabei et al. (2025)	Hierarchical cloud-edge processing	Industrial IoT plants	Medium	Data latency handling	Microservices + API gateways	Edge nodes + cloud AI.	Hybrid integration layer	Fit ↑ scalability
Sekar et al. (2025)	Organizational AI readiness	Enterprises (large manufacturing)	High cross-functional	Knowledge management integration	Maturity assessment model	Capability evaluation framework	Self-assessment tools	Fit predicts AI success
Shaban et al. (2025)	Comprehensive maintenance 4.0 review	Global industries	Cross-sector	Integration of ICT and human factors	Bibliometric + conceptual analysis	Digital capability taxonomy	Strategic roadmaps	Fit aligns ICT with org needs
Said et al. (2025)	Analytical framework linking IPT + AI.	Multi-tier supply networks	High network interdependence	High-volume data filtering	Hybrid ML + benchmarking	Analytical pipeline design	Results → decision systems	Fit ↑ SC resilience
Makkonen (2021)	Foundational IPT review applied to maintenance	Conceptual	N/A	Information requirements taxonomy	Literature synthesis	Theoretical foundation	Conceptual model linking IPR and IPC.	Fit forms basis for current study

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TABLE 4 Comparative fit analysis of information-processing mechanisms across uncertainty archetypes.

Dominant uncertainty profile	Superior IPC mechanism	Reason for superiority (IPT alignment rationale)
Structural uncertainty + interacting multi-component degradation	Digital twins (DT)	DTs convert structural ambiguity into counterfactual model knowledge, increasing IPC richness and reducing equivocality
High-latency/bandwidth constrained remote distributed assets	Edge/Federated learning (FL)	Decentralized learning enhances IPC by reducing communication load and improving local autonomy without compromising confidentiality
High signal noise/non-stationary multi-sensor environments	Advanced multi-sensor fusion and DL	Fusion reduces equivocality by integrating heterogeneous signal representations, increasing interpretive IPC depth
Multi-actor/multi-asset coordination complexity	Agentic/multi-agent orchestration	Multi-agent decision decomposition improves coordination IPC and translation layer efficiency

universally optimal; mechanism effectiveness is contingent on the dominant uncertainty driver. Table 4 synthesizes the comparative superiority of mechanisms under distinct uncertainty regimes, demonstrating that mechanism-level IPC contribution is conditional rather than uniform.

This comparative insight shows that “Fit” is not dependent solely on mechanism sophistication but on mechanism–uncertainty alignment. Therefore, the IPT-based design implication is not “select the best method” but “select the best mechanism conditional on the uncertainty class”. This elevates Table 1 from descriptive allocation to explanatory causal contingency logic.

Based on Tables 1–3, it is clear that recent research across mechanical, energy, and cross-domain maintenance contexts overall supports the foundational premise of the offered IPT framework. Across a range of domains—from electro-mechanical equipment and wind turbines to distributed IoT-based systems—research confirms that task complexity, environmental volatility, and subsystem interdependence all contribute collectively to determining the extent and diversity of information-processing requirements (IPR) that maintenance systems will need to cope with. Consequently, these requirements have driven the creation of matching information-processing capacity (IPC) functionality such as multi-sensor fusion, digital twins, deep learning ensembles, federated edge learning, and agent-based orchestration.

There is an evident trend arising from the mashup: systems that coordinate their IPRs with adequate IPC—be it high-fidelity digital twins for resolving uncertainty, explainable AI for operator trust, or decentralized edge learning for controlling latency—repeatedly report improved performance outcomes. These consist of greater fault-detection accuracy, longer lead times for prognostics, fewer false alarms, less downtime, and improved organizational responsiveness. Conversely, misfit examples such as data-limited environments that do not have adequate model interpretability or incomplete integration with enterprise maintenance systems demonstrate that technically advanced mechanisms provide limited operational benefit in the absence of structural correspondence to information-processing requirements.

Thus, Tables 1–3 offer the empirical basis for the causal logic illustrated in Figure 2, supporting the chain from Maintenance Task Characteristics, Environment, and Interdependence → Information-Processing Requirements → Mechanisms and Capacity → Translation Layer → Outcomes. The evidence supports the key theoretical assertion of this paper: that information-processing fit—the alignment of the level of uncertainty-driven demand with the capacity used to process it—is the key determinant that connects intelligent diagnostic technologies to maintenance and organizational performance. The next Section 4.3 makes these connections formal through directional propositions and testable hypotheses.

4.3 Core relationships and propositions

The model suggests a directional chain:

$$(\mathrm{MTC}, \mathrm{MTE}, \mathrm{MTI}) \rightarrow \mathrm{IPR} \rightarrow \mathrm{IPC}\ (\mathrm{Mechanisms}) \rightarrow \mathrm{Translation} \rightarrow \mathrm{Outcomes}$$

with Fit serving as the mid-level mediator/moderator that specifies whether IPC operates under specified IPRs. This sequential connection mirrors how maintenance task properties and environmental contingencies together influence information-processing demands, whose presence instigates the design and deployment of appropriate mechanisms.

Proposition 1: *(Uncertainty → Requirements)*. Increased task complexity, environment noise, and subsystem interdependence raise IPR levels demanding greater sensing resolution, wider fusion, tighter latency, higher interpretability, and more robust coordination. Examples: multi-signal rotor monitoring and long-horizon gearbox prognosis (Mailula and Saha, 2025a; Xu et al., 2025).

Proposition 2: *(Mechanisms → IPC)*. Mechanisms enhance IPC in complementary manners: fusion and higher-order DL facilitate contextual integration; DTs eliminate structural uncertainty and make counterfactuals possible; federated/edge learning enhances latency and confidentiality; agentic orchestration supports coordination and prescriptive action mapping. Modular composition (DT + edge filtering + fusion) case examples demonstrate tangible lead-time advantages (Intelligent wind gearbox studies; Xu et al., 2025).

Proposition 3: *(Fit → Outcomes)*. High fit between IPR and IPC results in better detection accuracy, longer predictable prognostic horizons, reduced false alarms, and better organizational outcomes. Misfit (under- or over-provisioning) generates rare operational gain in spite of technical accomplishment.

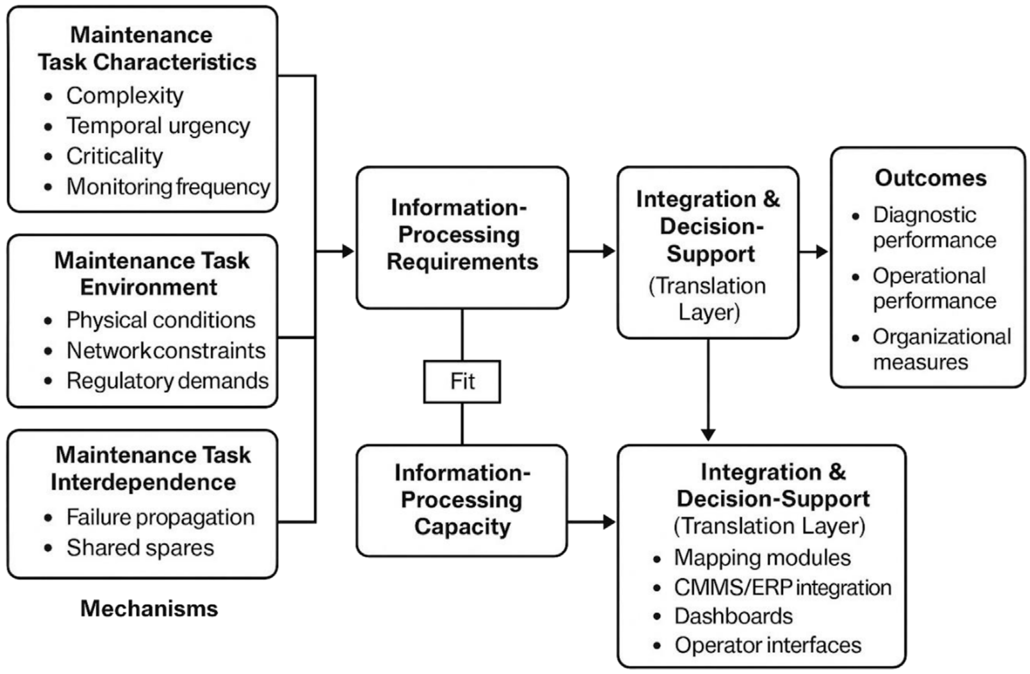

FIGURE 2
Theoretical model of the information processing theory framework for intelligent fault diagnosis and predictive maintenance.

Proposition 4: *(Necessity of Translation Layer).* Successful translation (diagnosis → prescriptive policy → operational action) is required for IPC improvements to yield organizational effects. Detection that is not integrated into CMMS/ERP and scheduling does not consistently decrease downtime: an observation that is reiterated in review and case-study publications.

Proposition 5: *(Governance and Skills Moderation).* Organizational governance, operator skill, and explainability needs moderate the IPC→Outcomes path; increased governance and skills enhance realized outcomes by facilitating appropriate action on predictions (Sekar et al., 2025; Shaban et al., 2025).

Proposition 6: *(Mechanism Complementarity).* Writing complementary mechanisms (e.g., DT for uncertainty structure + fusion for noisy modalities + edge for low latency) generates super-additive IPC performance when mechanisms cover orthogonal dimensions of IPR. Experimental results for SFTI-LVAE, DT-enhanced prognostics, and dual-graph GATs validate the complementarity assertion.

Figure 2 displays the theoretical model created in this research, inserting the IPT constructs into the field of intelligent fault diagnosis and predictive maintenance (PdM). The model depicts how Maintenance Task Characteristics, Task Environment, and Task Interdependence are antecedents that have an influence on Information-Processing Requirements (IPR) of intelligent maintenance systems.

These needs are subsequently satisfied by Information-Processing Capacity (IPC), which is achieved through technological and organizational arrangements including multi-sensor fusion, digital twins, federated or edge learning, and AI-agent orchestration. The alignment of IPR with IPC symbolizes the focal theoretical alignment that IPT introduces. An improved degree of alignment improves both the Integration and Decision-Support (translation) layer so that diagnostic outputs are satisfactorily translated into prescriptive maintenance actions.

Finally, the model illustrates how alignment of information-processing needs and capabilities enhances critical outcomes such as diagnostic accuracy, operation reliability, and organizational decision quality. This figure therefore gives a synthesis pictorial representation of the theoretical assertions laid out in Section 4.3.

The diagram shows the causal pathway from maintenance task precursors (characteristics, environment, interdependence) to information-processing need and capability, moderated by the "fit" construct. Mechanisms of integration and decision support make up the translation layer connecting technical diagnostic capability to organizational and operational performance.

4.4 Measurement and empirical operationalization

To be measured empirically (as operationalized in Section 3) for testing, constructs are measured as follows:

- MTC: asset sensor count, fault cardinality, needed prognostic horizon (hours/days), safety rating (scale).
- MTE: measured latency/bandwidth, environmental variability measures (temperature, vibration ranges), occurrence of explainability/regulatory flags (scale/binary).
- MTI: topology coupling index (number of coupled subsystems), spare sharing measure, failure propagation probability.

- IPR: expert-rated scales for required latency, fusion breadth, interpretability, and coordination; derived requirements from experimental task definitions.
- IPC: number/type of deployed mechanisms, ensemble breadth, DT fidelity score, edge inference latency (ms), federated participation rate.
- Translation: % automated prescriptive actions, alarm→action decision latency, CMMS integration level, scheduler optimization gain metrics.
- Outcomes: detection accuracy/F1/lead time/false alarm rate from experiments; downtime reduction %, MTBF change, and decision quality scores from logs and surveys.

A base operational formulation for an IPT Fit Index can be expressed as:

$$\text{IPT Fit Index} = 1 - \left(\frac{|IPR\ Score - IPC\ Score|}{Maximum\ Possible\ Gap}\right)$$

where IPR and IPC scores are normalized scales derived from the measurement constructs defined above. A value closer to one indicates high processing alignment (high fit); values approaching 0 indicate misalignment.

Mixed methods facilitate triangulation: laboratory and bench experiments provide system-level metrics; maintenance manager surveys yield perceptual measures (IPR, perceived fit, decision quality); case studies record translation flows and governance constraints.

4.5 Testable hypotheses

Phrased from propositions, empirically testable hypotheses for the empirical program are:

- H1. Higher MTC, MTE, and MTI are positively related to higher IPR scores.
- H2. Use of IPC mechanisms (fusion, DT, federated/edge, agents) raises measured IPC capacity.
- H3. Fit (congruence between IPR and IPC) mediates the relationship between IPC and Outcomes (detection accuracy, lead time, downtime reduction).
- H4. Translation capability moderates the IPC→Outcomes relationship; higher translation produces greater organizational gains.
- H5. Organizational governance and staff expertise moderate the Fit→Outcomes path; higher governance/skills amplify benefits from good fit.

4.6 Design implications and practical guidance

From the model, four practical design rules emerge:

1. Diagnose IPR before selecting mechanisms. Explicit mapping from MTC/MTE/MTI to IPR prevents over-engineering (heavy DL where interpretability and edge rules suffice) and under-engineering (insufficient fusion or DT for structural uncertainty).
2. Write complementary mechanisms. Stack DTs for structural counterfactuals, multi-sensor fusion for noisy multimodal inputs, and federated/edge paradigms for latency/privacy constraints.
3. Engineer the translation layer. Put money into mapping modules (diagnosis→risk→prescription), CMMS/ERP integration, and operator workflows. Translation is the critical pipeline for technical performance to drive downtime metrics.
4. Track Fit as a KPI. Keep an operational fit index and design system iteratively until fit thresholds correspond to target operational KPIs (e.g., downtime reduction, MTBF gains).

Here the IPT-based theoretical model is made formal for intelligent fault diagnosis and PdM that relates task characteristics, environment, and interdependence to explicit information-processing requirements; lists mechanisms that provide IPC; and emphasizes fit and translation as key determinants of outcomes. The model is purposely functional: it offers quantifiable constructs, empirically testable hypotheses, and prescriptive design recommendations congruent with the above-noted mixed-method approach. By linking system-level experimental measures to organizational survey indicators and case data, the IPT framework provides a stringent means for theoretical validation and practical architecture design within PdM systems.

5 Theoretical and practical implications

The framework for intelligent fault diagnosis and predictive maintenance (PdM) proposed in the IPT contributes both to theory development and practice in industry through providing an integrated perspective on how uncertainty, task characteristics, and decision architectures are interrelated to influence maintenance performance. This section expands the wider implications of the framework over two dimensions:

a. theoretical progress in IPT within the scope of intelligent industrial systems,
b. actionable design and managerial recommendations for practitioners deploying and creating PdM solutions.

5.1 Theoretical implications

5.1.1 Applying information processing theory to cyber-physical environments

Traditional IPT (Tushman and Nadler, 1978) and its organizational applications were crafted to account for how companies' structure to manage information uncertainty. The current model applies that reasoning to cyber-physical and AI-based maintenance settings, wherein information is not confined to human communication but streams perpetually between sensors, digital twins, and decision-making agents.

By translating sensors, edge devices, and AI agents into organizational subunits with cognitive functions, the model reframes IPT's constructs which includes uncertainty, requirements, capacity, and fit into machine-intelligence systems.

This re-framing develops the theory from organizational design to data-driven system design, illustrating that the theoretical principles of information-processing alignment are sustained even with partially automated cognitive labor.

5.1.2 Re-defining "fit" as a multi-layer construct

Classic IPT literature tends to see fit as a managerial or structural attribute. The presented framework establishes fit concurrently at three levels:

- Technical fit, correspondence of data features and model capabilities (e.g., breadth of fusion, fidelity of DT, tolerance of latency).
- Organizational fit, congruence of analytical results and decision processes (e.g., integration with CMMS, interpretability by operators).
- Ecosystem fit, coordination of decentralized maintenance nodes via federated and multi-agent architectures.

This multi-layered articulation of IPT makes it more refined by acknowledging that, in smart maintenance, information processing is nested. The sufficiency of one layer (e.g., algorithmic precision) relies on congruence with the next (e.g., decision implementation). The architecture thus enlarges IPT's purpose from intra-organizational alignment to multi-layer and boundary-spanning coordination.

5.1.3 Combining cognitive and computational perspectives of information capacity

In organizational theory, IPC has mostly been understood as human cognitive or structural ability. This research reconceptualizes IPC as a hybrid cognitive–computational ability that includes both algorithmic mechanisms (deep learning, digital twins, federated learning) and organizational cognition (human sense-making, governance, interpretive systems). Embedding machine learning and AI mechanisms into the IPT framework, the theory integrates information systems and operations management theories to provide an integrated perspective of how organizations and technologies co-produce information capacity.

5.1.4 Mechanism complementarity and the resource-based view

The hypotheses on mechanism complementarity (P6) create theoretical complementarity between IPT and the resource-based view (RBV). In RBV, distinctive resource combinations create enduring advantage; in IPT, complementary mechanisms collectively extend processing capacity to meet emergent requirements. The empirical hypothesis that compositional architectures (DT + Fusion + Edge) are superior to single mechanisms indicates that fit is not additive but super-additive, providing a theoretical transition from organizational resource bundling to information-processing alignment.

5.1.5 Offering a quantifiable bridge between organizational and technical results

Previous PdM research mostly halts at algorithmic measures of accuracy, with organizational implications left implicit. The IPT model brings measurable constructs—fit, translation effectiveness, and decision quality—to account, connecting technical performance with organizational reliability results. This operationalization bridges the gap in IPT from descriptive theory to testable performance framework. The empirical strategies outlined (SEM between system-level and organizational variables) offer a means for measuring how better sensing and analytics in cascade to improve managerial effectiveness, thus increasing IPT's explanatory power.

5.1.6 Framing uncertainty as a stimulator instead of a hinderance

Lastly, the framework recasts uncertainty as a positive state rather than a negative one, a spur to architectural innovation. With every increase in environmental complexity comes the concomitant increases in processing capacity through architectural adaptation. This dynamic perspective adds depth to IPT by bringing in evolutionary logic—organizations (and smart systems) do not just adapt to uncertainty but learn and reorganize about it. In this respect, the framework adds a dynamic-capabilities extension of IPT for cyber-physical systems.

5.1.7 Theoretical extension of IPT in CPS-based PdM context

This expansion of IPT to cyber-physical predictive maintenance environments extends it beyond the original domain of organizational cognition. In classical IPT, the information-processing units were mainly human decision actors, supported by structure. In CPS-driven PdM, information-processing functions are shared between human and computational elements, such as Digital Twins, multi-sensor fusion architectures, federated learning nodes, and AI-agent orchestration mechanisms. It thereby reframes IPT to accommodate hybrid cognitive units whereby computational intelligence performs the sensing, learning, inference, and decision coordination roles traditionally undertaken by human managerial cognition.

The notion of "fit" also extends from an organization-structure alignment to a multilayer construct comprising: (i) technical fit, or mechanism capability alignment with task uncertainty; (ii) organizational fit, or translation layer and workflow alignment; and (iii) ecosystem fit, or cross-enterprise coordination capability. This multilayer interpretation becomes important because PdM value is realized only when alignment is achieved simultaneously across these levels.

Finally, IPC within this expanded IPT formulation is a hybrid computational-organizational capability that integrates sensing/analytics richness, simulation-based reasoning competence, with distributed learning autonomy, and human interpretive governance. This extension advances IPT theoretically by showing that IPT's principles remain applicable when cognitive labor is algorithmically distributed across machines, agents, humans, and networks rather than being centered in human managerial cognition alone.

5.2 Practical implications

In addition to theoretical insights, IPT's framework contributes concrete, actionable advice to practitioners who wish to design or enhance intelligent maintenance systems. These implications range across system architecture, managerial choice, and policy development.

5.2.1 Diagnostic alignment and architecture design

The first empirical implication is the diagnosis of information-processing needs prior to mechanism choice. Most PdM implementations are unsuccessful because they deploy advanced algorithms without considering if such capability is commensurate with the uncertainty they encounter. The approach suggests a systematic diagnostic phase that measures task complexity, environmental variance, and subsystem interdependence to arrive at explicit IPR profiles. These profiles inform mechanism choice like applying lightweight edge models for low-variability assets, whereas employing DT-fusion architectures to high-interdependence systems. This ensures economically efficient and purpose-suitable investments.

5.2.2 Mechanism composition for scalable capacity

The complementarity principle in the model guides modular assembly of mechanisms. Practitioners should combine digital twins for counterfactual reasoning, multi-sensor fusion for shared situational awareness, and federated learning for decentralized collaboration. Orchestrated through AI agents, these modules create adaptive ecosystems that preserve diagnostic accuracy as conditions change. This practice facilitates incremental scalability where organizations scale incrementally by adding modules as complexity grows instead of replacing entire systems.

5.2.3 Translating the translation layer

The “translation layer” is too often overlooked but an essential connection between analytics and action. In practice, organizations should invest in:

- CMMS/ERP integration so that fault diagnosis alerts automatically create maintenance work orders;
- Dashboard decision-latency tracking measuring the delay between fault detection and corrective action; and
- Human-in-the-loop feedback mechanisms to record operator judgments to retrain models.

These practices instantiate the IPT observation that capacity for information produces value only when outputs get translated into timely, trustworthy decisions. Installing measurable “translation KPIs” (e.g., response time average, ratio of automated actions) transforms high-level theory to day-to-day improvement metrics.

5.2.4 Governance, skills, and explainability

The model stresses that skill levels and governance moderate the efficacy of technological mechanisms. In practice, companies need to create governance structures that delineate data ownership, model accountability, and ethical application of AI forecasts. Operator education needs to upgrade literacy in AI interpretation, mapping human and machine cognition. Explainable-AI software can image model reasoning, enhancing trustworthiness and adherence to safety rules. Together, these interventions lead information capacity from a technical competence to an organizational competency.

5.2.5 KPI-based fit monitoring

The concept of “fit” can be operationalized in the form of a management key performance indicator (KPI). Maintenance organizations can calculate a fit index by dividing measured IPR (derived from uncertainty and interdependence metrics) with observed IPC (mechanism performance, latency, interpretability). Ongoing monitoring of this index enables early detection of misalignments such as under-capacity (too little analytics) or over-capacity (duplicate complexity). In practice, optimal fit minimizes wasted investment and aligns technical sophistication with true business requirements.

5.2.6 Collaboration and data-governance models

Both the federated-learning and multi-agent aspects of the IPT framework have straightaway implications for cross-organizational collaboration. Clients, service providers, and equipment manufacturers can collaboratively train diagnostic models together without exchanging proprietary data, maintaining confidentiality while enhancing predictive accuracy. This practice aligns with the new norms of regulation on data sovereignty and offers a model for industrial data-sharing consortia. The IPT form explains that such collaborations extend collective IPC, achieving network-level fit for all participants.

5.2.7 Policy and infrastructure planning

For policymakers and planners of infrastructure, the model gives instruction on how to design digital-readiness programs. Investments in edge-computing clusters, broadband, and ontologies of standard data increase national IPC through minimizing latency as well as interoperability obstructions. Governments can incentivize corporations to incorporate IPT-compatible architectures, those that record IPR-to-IPC mapping and keep auditable logs of decisions. This enhances industrial resilience as well as regulatory transparency in AI-aided maintenance.

5.2.8 Benchmarking and continuous learning

The IPT framework accommodates benchmarking and organizational learning. By organizing maintenance performance in terms of IPR, IPC, fit, and translation measures, organizations are able to compare plants, lines, or subsidiaries on common measures. The openness promotes cross-site learning and capability transfer. Coupled with digital-twin simulations, companies can conduct “what-if” analyses to see the impact of varying task complexity or environmental turbulence on required processing capacity and making maintenance a learning function instead of a fixed support process.

5.2.9 Organizational translation and governance imperative

In PdM deployments, the organizational translation mechanisms-structured explainability routines, maintenance decision protocols, and operator decision support training-play a crucial role in the benefits realized from technical investments in IPC. Indeed, even the best technical mechanisms-technical DT, FL, and fusion-yield weak operational improvements if the organizational governance, role clarity, and interpretive capability building is underdeveloped. Hence, the implementation of IPT-based PdM mandates parallel building of organizational capability-skill development, governance frameworks, CMMS linkages, and standardization of interpretive guidelines-to ensure that information-processing capacity translates into sustained value for an organization.

Collectively, these implications represent the IPT framework both as a theoretical integration platform and as a managerial design instrument. Theoretically, it integrates cognitive, computational, and organizational levels of information processing into a unified explanatory framework. Practically, it converts those relationships into quantifiable design variables and performance metrics that inform architecture, governance, and policy. By making clear connections among uncertainty, mechanism design, translation, and fit, the framework enables researchers to test rich hypotheses and allows practitioners to construct more adaptive, open, and lean maintenance ecosystems. In so doing, it closes the artificial gap between technological complexity and organizational relevance which is the core problem of intelligent fault diagnosis and predictive maintenance.

6 Conclusion, limitations, and future research

This research outlined an Information Processing Theory (IPT)–grounded framework for smart fault diagnosis and predictive maintenance (PdM) that systematically connects uncertainty sources, task characteristics, and interdependence to the mechanisms and organizational abilities that process information in industrial systems. The proposed framework reframes predictive maintenance as a problem of information processing, highlighting that successful solutions emerge not only from algorithmic accuracy but from how well information-processing requirements (IPR) are matched with information-processing capacity (IPC). Through structures like maintenance task characteristics, environment, interdependence, translation layers, and fit, the model encapsulates both the technological and organizational aspects of decision excellence in PdM ecosystems. Through the incorporation of mechanisms like digital twins, multi-sensor fusion, federated/edge learning, and AI-agent orchestration, the framework provides a systematic grasp of how distributed intelligence improves maintenance performance, reliability, and decision-making support. Theoretical advances expand IPT into the cyber-physical space, reframing it as a dynamic data-driven theory of coordination among human and machine agents. Operationally, the framework offers prescriptive design principles such as diagnosing IPR prior to mechanism choice, synthesizing complementary modules, engineering translation layers, and monitoring fit as a key performance index, that allow firms to both achieve technological effectiveness and organizational adaptability. Together, these findings place the IPT framework as a solid theoretical underpinning and managerial design framework for intelligent, explainable, and high-reliability maintenance systems.

Although it has a broad scope, this study has a number of inherent drawbacks. The propositions and framework are formulated from literature and case-based data that, although varied, have a possibility to overemphasize mature industrial economies like manufacturing and energy and underrepresent less digitalized fields. Empirical generalizability can thus be limited since laboratory experiments and controlled data cannot adequately mimic the complexity, uncertainty, and socio-technical realities of large-scale industrial settings. Measurement validity is also a challenge, as the operationalization of abstractions IPT constructs like IPR, IPC, and fit depends on the opinion of experts and proxy measurements that are prone to subjective bias and contextual variation. Also, fast-changing technology in AI, edge computing, and explainability tools can change the applicability or implementation of some mechanisms with time, requiring constant reframing of the framework. The research design also suffers from possible endogeneity and causality constraints; for example, companies with better governance or digital sophistication will likely have higher fit by default, tainting causal inference. Lastly, although governance, skill, and interpretability factors are accounted for, wider socio-technical and ethical concerns such as workforce migration, algorithmic responsibility, and cybersecurity in federated infrastructures lie outside this paper's analytical purview and deserve separate investigation.

Future studies ought to extend this framework through cross-sector, longitudinal, and experimental verification to test empirically and sharpen the hypothesized associations among uncertainty, mechanisms, fit, and outcomes. Field research across sites and A/B testing in real-world settings can confirm causality as well as unveil the temporal dynamic adaptation of fit, while measurement instruments standardized for IPR and IPC can augment construct validity and allow benchmarking across firms. Researchers must also investigate causal inference techniques and digital-twin–based counterfactual modeling to assess the marginal value of predictive and prescriptive choices. Future research must also analyze the human and governance elements of IPT in PdM that explains how operator explainability, trust calibration, and federated governance affect translation success. Combining economic and policy viewpoints using cost–benefit modeling, data-sovereignty analysis, and interoperability standards research can broaden the framework's usability to large industrial ecosystems. Finally, future research should develop the IPT model into a dynamic capability platform for adaptive industrial intelligence to facilitate predictive maintenance systems that learn, align, and adapt continuously under shifting technology and environmental states.

The IPT framework described here offers a structured, testable, and applied blueprint for information-processing requirement versus capacity alignment in intelligent maintenance systems. By making the causal connections between task antecedents, mechanism design, translation, and fit explicit, the framework brings predictive maintenance to a mature, socio-technical science in which algorithmic quality is paired with quantifiable organizational value. The research agenda outlined here grounded in mixed methods, field experiments, and strong measurement and provides a promising avenue for researchers and practitioners to collaboratively design PdM systems that are not just predictive but prescriptive, transparent, and operationally relevant.

6.1 Future research extensions based on IPT contingency logic

Based on the theoretical model and IPT contingency grounding, the following are suggested lines of further study:

- *Mechanism Performance under Specific Uncertainty Archetypes:* Empirical benchmarking of DT-based, FL-based, and Fusion-based frameworks for clearly defined uncertainty categories with respect to conditional superiority and mechanism fit optimization, such as data-level noise, structural coupling, and communication bandwidth constraints.
- *Formal Development of an IPT Fit Index KPI:* Quantitative operationalization, calibration, and optimization of an IPT Fit Index that dynamically measures the congruence of IPR and IPC across different industrial contexts, with the ability to track the real-time fit and design adaptive architecture.
- *Latency Elasticity of the Translation Layer:* Building mathematical models to quantify how latency in translation-i.e., translating diagnosis into prescription and then execution-affects degradation progression and reduces downtime by providing elasticity coefficients for management decision design.
- *Cross-Industry Mechanism Complementarity Validation:* Comparative multi-sectoral empirical studies in industries such as energy, rail, discrete manufacturing, maritime, and automotive to validate if mechanism complementarity yields consistent super-additive IPC performance across industrial settings (DT + fusion + edge).

These research directions transcend broad conceptual suggestions to develop precise, testable, and domain-specific empirical paths that advance the IPT-driven PdM research agenda directly.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

DD: Writing – review and editing, Conceptualization. OA: Methodology, Writing – original draft.

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