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Assessing Automation Levels and Technological Prerequisites for IIoT Connectivity in Textile and Garment Enterprises: Orientations for Predictive Maintenance in Smart Factories

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ABSTRACT: This study examines automation levels and technological prerequisites for Industrial Internet of Things (IIoT) connectivity to propose predictive maintenance (PdM) adoption orientations for Vietnamese textile and garment enterprises. Based on survey results collected, processed, and synthesized by the research team, the study combines descriptive statistics, comparisons across spinning, weaving, dyeing, and garment manufacturing, a targeted literature review, and conceptual architecture design. The findings reveal uneven adoption of technologies supporting data acquisition, processing, integration, and production management, with notable differences across subsectors. By linking these findings to PdM implementation requirements, the study proposes a four-layer IIoT–PdM architecture, subsector-specific equipment priorities, and a phased implementation roadmap. The proposed framework provides a basis for prioritizing technological investments and designing subsequent pilot studies. Its predictive performance and economic benefits require validation using actual operating and maintenance data.

KEYWORDS: automation, Industrial Internet of Things, predictive maintenance, artificial intelligence, Vietnam's textile and garment industry

1. INTRODUCTION

Spinning, weaving, dyeing, and garment production lines differ in their mechanical, electrical, and control configurations, and consequently in their exposure to unplanned downtime. Failures involving motors, bearings, drive systems, circulation pumps, or control assemblies may interrupt operations and increase scrap and maintenance costs. Data-driven asset management is therefore an important direction as enterprises gradually transition toward smart factories. However, the feasibility of predictive maintenance depends not only on equipment automation but also on signal acquisition, data connectivity, condition analysis, and integration with maintenance management processes. A highly automated production line does not necessarily provide the historical data required by predictive algorithms. Evaluating automation levels alongside underlying technological prerequisites is thus necessary to identify implementation pathways for Industrial Internet of Things (IIoT)-based predictive maintenance (PdM) appropriate to textile and garment manufacturing.

The research team's 2024 survey and synthesis of Vietnam's textile and garment industry documented automation levels and the use of sensors, digital technologies, and production management software across four subsectors. The data suggest uneven modernization across enterprise groups and production stages. Nevertheless, these indicators have not been systematically linked to PdM implementation requirements. IIoT enables operating data to be collected and exchanged between equipment and monitoring systems. The cyber-physical systems architecture proposed by Lee et al. [1] illustrates how multiple information layers can be interconnected to support manufacturing decisions. In maintenance, Jardine et al. [2] emphasize condition monitoring, diagnostics, and prognostics, while the reviews by Carvalho et al. [3] and Zonta et al. [4] indicate that machine learning can support anomaly detection, fault classification, and degradation prediction when suitable data are available.

Research on Industry 4.0, cyber-physical systems, and predictive maintenance provides a theoretical basis for acquiring, integrating, and analyzing equipment data [1]–[5]. However, translating these principles into implementation guidance tailored to the technological conditions of each textile subsector requires further clarification. In particular, existing indicators of automation, sensor adoption, and management software have not been fully examined as potential enablers and constraints of PdM. Accordingly, this study pursues three objectives: (i) to assess automation levels and digital technology conditions in spinning, weaving, dyeing, and garment manufacturing; (ii) to identify the technical requirements linking existing technological conditions to the components of an IIoT–PdM system; and (iii) to propose an integrated architecture, subsector-specific application priorities, and a verifiable implementation roadmap. Its contribution is to translate an assessment of current conditions into technology design and implementation orientations, rather than to develop or test a new fault-prediction algorithm.

2. RESEARCH CONTENT

2.1. Automation, IIoT connectivity, and predictive maintenance

Automation refers to the ability of equipment to perform operations, control actions, or process monitoring with reduced direct human intervention. IIoT connectivity additionally requires data export, communication, synchronization, data protection, and interaction with external systems. Accordingly, highly automated equipment does not necessarily support the sharing of historical data needed for predictive maintenance.

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PdM combines equipment condition data with analytical models to identify signs of deterioration and support intervention before failure occurs. Predictive capability depends jointly on meaningful measurements, historical failure records, alert verification procedures, and maintenance execution arrangements. An anomaly-alert model is not equivalent to a model that accurately predicts failure time or remaining useful life (RUL) [2]–[4].

Industry 4.0 technologies are often adopted unevenly across manufacturing enterprises; the integration of operational technologies with data platforms is addressed by Frank et al. [5]. Because connectivity-quality data are not available, the present study does not construct a new composite IIoT index. Instead, it examines technological components potentially related to implementation capability. Three groups of prerequisites are distinguished. The first comprises data acquisition conditions, including sensors, controllers, and equipment-state recording. The second concerns connectivity and data processing, including communication interfaces, storage infrastructure, edge or centralized processing, and intersystem information exchange. The third covers maintenance applications and governance, including historical failure data, management software, technical personnel, and decision-making procedures. These conditions are complementary rather than interchangeable. Survey scores for individual technologies are therefore treated only as preliminary indicators, not as evidence that comprehensive PdM implementation is feasible.

2.2. Research design, data, and analytical methods

2.2.1. Data sources and survey scope

The study uses survey findings collected, processed, and synthesized by the research team for enterprises in the spinning, weaving, dyeing, and garment manufacturing subsectors. The survey addressed equipment sophistication, automation of production operations, Industry 4.0 technology adoption, and management software systems. The indicators selected for the present paper comprise: (i) equipment and process automation levels; (ii) the use of sensors, mobile devices, and data-processing technologies; and (iii) the use of manufacturing execution systems (MES) and enterprise resource planning (ERP). These indicators were chosen to examine the technological foundations of IIoT connectivity and PdM adoption.

The research team aggregated and analyzed the survey by four textile and garment subsectors: spinning, weaving, dyeing, and garment manufacturing. The surveyed sample comprised 98 enterprises, including 29 spinning, 15 weaving, 19 dyeing, and 35 garment enterprises. The survey focused on production-process automation, digital technology adoption, and production management systems. Results were aggregated by subsector and indicator using a five-point scale.

2.2.2. Measurement scale and data processing

Automation and technology-adoption indicators were aggregated according to the survey instrument's five-point rating scale. Each indicator score represents an assessed level of technological application under the instrument's measurement conventions; it does not directly indicate the percentage of enterprises that have implemented the corresponding technology. Results were compiled for each subsector and for the full sample. Comparisons between scores identify differences in technology use, but are not interpreted as evidence of causal relationships or actual technical integration among systems.

The mean scores reported are the research team's processed survey results on a five-point scale, rounded to two decimal places. Subsector and overall scores are used for descriptive statistics, including differences between related technology groups. These differences indicate only variation in the surveyed technology-adoption indicators; they cannot be interpreted as enterprise ownership rates, degrees of intersystem integration, or causal effects.

2.2.3. Analytical approach and architecture development

The study employs descriptive statistics to analyze technology adoption and compare the four subsectors; comparative analysis to identify gaps between data-acquisition, data-processing, and production-management technologies; and literature synthesis to establish the basic technical requirements of IIoT–PdM systems. Survey findings are then mapped to architectural layers to propose arrangements for connectivity, data processing, analytics, and maintenance governance. A phased implementation roadmap is developed, progressing from data preparation and condition monitoring to model trials and management integration. As the proposed architecture has not been tested on an operating production line, predictive performance and economic effectiveness must be assessed in subsequent implementation studies.

Table 1. Analytical framework for technological prerequisites for IIoT–PdM

Prerequisite group	Observed indicator	Items requiring verification
Signal acquisition	Sensors; equipment automation	Data frequency, quality, and export capability
Processing infrastructure	Mobile devices; cloud computing/big data	IIoT interoperability and historical data
Operations management	MES; ERP	Integration with CMMS and maintenance records
PdM analytics	No directly measured indicator	Alert accuracy and RUL prediction

Source: Author's framework based on the analysis and studies on cyber-physical system architectures, condition monitoring, and predictive maintenance [1]–[4].

2.3. Research findings and discussion

2.3.1. Automation differences across subsectors

Automation in textile and garment enterprises must be assessed in relation to subsector-specific technologies, given substantial differences in machinery, manufacturing operations, and work-in-process handling. This study therefore examines representative processes to identify uneven automation and derive requirements for data acquisition and equipment selection in condition monitoring.

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Survey findings indicate relatively high automation in several spinning operations: bale opening scored 4.50/5, sliver-can replacement 4.36/5, and doffing at ring-spinning machines 3.90/5. Yarn piecing at ring-spinning machines, however, scored only 2.52/5. Work-in-process transfer received lower scores; for example, transfer from carding to the first drawing stage on a carded-spinning line scored 1.97/5. Automation of individual machines therefore does not ensure synchronization across an entire production line.

In weaving, automation scores were 1.67/5 for warp-beam preparation, 1.80/5 for replacing weaving beams and yarn packages, 1.67/5 for fabric doffing and fabric-roll transport, and 2.33/5 for shuttle-changing operations. These scores suggest that enterprises should first examine existing data-acquisition capabilities and the feasibility of retrofitting measurement systems to older equipment before deploying digital monitoring.

In dyeing, automation varied considerably across processes. In quality control, fabric dyeing scored 2.89/5, compared with only 1.42/5 for textile printing. Automation of chemical and dye feeding to machines scored 3.21/5. In dyeing and finishing lines, setting process parameters on machines scored 3.53/5, whereas integrated information systems between machines scored 2.58/5. These differences indicate that automated control in certain operations has not been matched by comparable adoption of integrated information systems. This finding highlights connectivity and data-standardization requirements when planning equipment condition monitoring.

In garment manufacturing, fabric spreading scored 3.97/5 and cutting 3.38/5, compared with 2.41/5 for numbering and bundle separation. Notably, work-in-process transport from cutting to sewing scored only 1.22/5, while transfer from sewing workshops to packaging scored 1.16/5. These results show an imbalance between production-equipment automation and interprocess material handling. IIoT–PdM implementation should therefore prioritize critical assets capable of generating relevant data while separately assessing connectivity and monitoring needs for each equipment category.

Representative automation indicators for dyeing and garment manufacturing are summarized in Table 2. The scores describe automation in different operations and production functions, highlighting within-subsector variation. As the selected indicators are not fully comparable in technological function, they are used for descriptive analysis rather than direct ranking of overall automation across the two subsectors.

Table 2. Automation levels in selected dyeing and garment manufacturing operations

Subsector	Operation/equipment	Automation score
Dyeing	Quality control in dyeing operations	2.89
Dyeing	Quality control in textile printing	1.42
Dyeing	Feeding chemicals and dyes into equipment	3.21
Dyeing	Setting machine process parameters	3.53
Dyeing	Integrated information systems between machines	2.58
Garment manufacturing	Fabric spreading	3.97
Garment manufacturing	Cutting	3.38
Garment manufacturing	Numbering and bundle separation	2.41
Garment manufacturing	Work-in-process transfer from cutting to sewing	1.22
Garment manufacturing	Transfer from sewing workshop to packaging	1.16

Source: Research team survey results, 2024.

Taken together, the findings reveal uneven automation across operations in all four subsectors. In spinning, several core processes are relatively automated, whereas work-in-process transportation remains limited. Weaving scores are low for preparatory operations, component replacement, and handling. In dyeing, the automation of process-parameter settings exceeds the adoption of integrated interequipment information systems. In garments, spreading and cutting are more automated than interprocess transportation. Automation therefore develops unevenly across production functions, requiring equipment-specific data-acquisition and condition-monitoring solutions. Because the representative indicators are not fully equivalent across subsectors, the study does not use them to rank overall subsector automation.

2.3.2. Sensor and data technology prerequisites

Table 3. Industry 4.0 technology adoption in textile and garment enterprises, 2024

Subsector	Mobile	Cloud/big data	Sensors	Image/voice recognition	Robotics
Spinning	3.79	2.97	3.97	2.38	3.59
Weaving	2.87	2.40	2.80	2.27	2.47
Dyeing	2.89	2.37	3.00	2.16	2.21
Garment	3.45	2.77	3.23	2.22	2.22
Overall	3.25	2.63	3.25	2.26	2.62

Source: Research team survey results, 2024.

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Table 3 shows that sensors and mobile technologies share the highest mean adoption score (3.25/5 each), while cloud computing/big data scored 2.63/5 and image/voice recognition 2.26/5. The 0.62-point gap between sensors and cloud computing/big data reflects differences in their adoption levels within the survey sample. These results suggest a need to examine data management and integration, but do not establish the extent of interoperability between enterprise equipment and information systems. Cloud computing is not mandatory in every PdM architecture: some applications process data at edge devices or on-premises servers. Thus, a lower cloud/big-data score than the sensor score does not demonstrate that enterprises lack PdM capability. What matters is whether equipment condition data can be accessed, stored, processed, and linked to operating records and maintenance events.

Spinning scored 3.97/5 for sensors and 2.97/5 for cloud computing/big data, a 1.00-point difference. The corresponding differences were 0.40, 0.63, and 0.46 points in weaving, dyeing, and garments, respectively. These results warrant investigation of sensor-data export, time stamping, synchronization by machine identifier, and historical storage. Without these conditions, machine-learning applications may encounter difficulties as early as dataset construction.

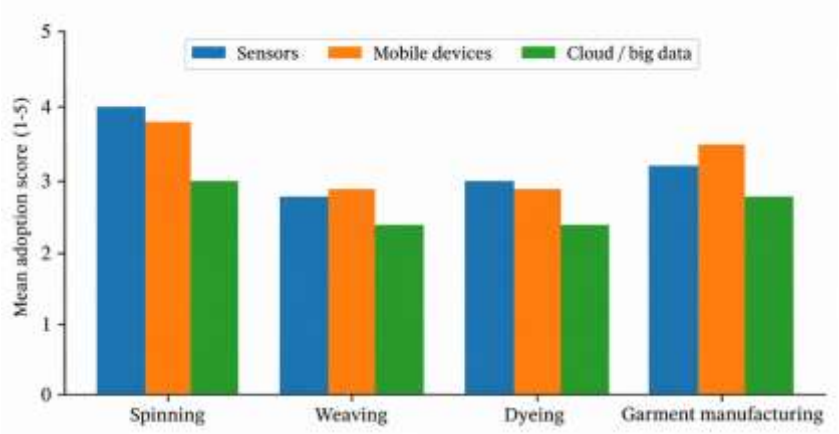

Figure 1. Comparison of sensor, mobile device, and cloud/big data adoption by subsector
Source: Research team survey results, 2024.

Two technological priorities follow from these results. Where equipment already has sensors and data-export capability, efforts should focus on standardizing connection interfaces, synchronizing data, and establishing operating histories. Where equipment lacks appropriate measurement systems, additional sensors and data-acquisition devices may be considered. The choice must be based on equipment characteristics and monitoring requirements, not merely on mean subsector sensor-adoption scores.

2.3.3. MES, ERP, and integration with maintenance management

Table 4. MES and ERP adoption in textile and garment enterprises

Subsector	MES	ERP
Spinning	2.79	3.24
Weaving	1.89	1.60
Dyeing	2.37	2.11
Garment	3.67	3.43
Overall	2.68	2.59

Source: Research team survey results, 2024.

As shown in Table 4, mean adoption scores were 2.68/5 for MES and 2.59/5 for ERP. Garment manufacturing had the highest MES score (3.67/5), whereas weaving scored 1.89/5. These ratings describe management-software adoption but do not indicate whether MES is linked to sensor signals or maintenance systems. In an IIoT–PdM environment, MES may provide machine status, work orders, and operating conditions; ERP can support resource, materials, and maintenance-related management where relevant modules exist; and computerized maintenance management systems (CMMS) focus on equipment records, failure events, schedules, and maintenance work orders. The presence of these applications alone does not demonstrate integrated maintenance data. Data exchange, information standardization, and procedures for verifying and responding to alerts remain decisive.

The 0.57-point gap between sensors and MES reflects different levels of adoption of these two technologies in the survey. It does not establish the degree of integration between equipment and production management systems. Before PdM implementation, enterprises should assess data exchange among machines, storage infrastructure, and maintenance management software. Integration may involve MES, ERP, CMMS, or an appropriate data platform and need not depend on a single software category.

2.4. Proposed IIoT–PdM architecture

Based on the findings, the study proposes an IIoT–PdM architecture addressing the principal technological requirements arising from uneven automation, data-acquisition capabilities, and adoption of production management systems. The four functional layers are designed for incremental deployment, reuse of existing equipment, and flexible integration with management applications. The distinctive feature is not the number of

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architectural layers but the connection between subsector-level survey findings and technology selection decisions. The model is conceptual and has not been implemented or experimentally validated.

Table 5 systematizes the relationships among survey findings, technical requirements, and design orientations. It provides a basis for determining the functions required of an IIoT–PdM architecture under uneven technological conditions across subsectors.

Table 5. Mapping survey findings to IIoT–PdM architecture requirements

Analytical finding	Technical requirement	Design orientation
Uneven automation across operations	Compatibility with multiple equipment generations	Flexible data acquisition for each machine type
Differences in sensor adoption between subsectors	Verify signal accessibility	Reuse existing sensors or retrofit measurements
Differences between sensors and data-processing technologies	Ensure data storage, processing, and retrieval	Combine edge processing, local servers, or cloud services
Uneven MES/ERP adoption	Avoid dependence on proprietary applications	Use open integration interfaces
No direct failure-history indicator	Develop data incrementally	Condition monitoring first; prediction later

Source: Author's proposal based on the analysis and literature on system architectures, condition monitoring, and predictive maintenance [1]–[4].

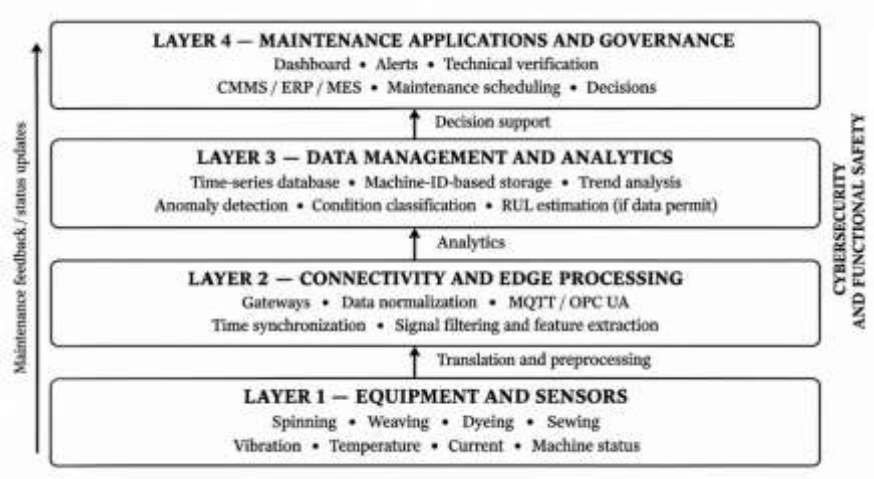

Figure 2. Proposed four-layer IIoT–PdM architecture for textile and garment enterprises
Source: Author's proposal based on theoretical literature on system architectures, condition monitoring, and predictive maintenance [1]–[4].

Figure 2 illustrates the four functional layers of the proposed IIoT–PdM architecture. Equipment condition data are acquired, transmitted, processed, and analyzed before being translated into information supporting maintenance decisions. The main data flow moves from equipment and sensors through connectivity and edge processing to analytics and applications. The feedback path from applications to equipment represents updates to operating status and maintenance outcomes, enriching data for subsequent cycles. It does not imply that an AI algorithm automatically controls or shuts down equipment. Information security and operational safety are considered across all four layers.

Layer 1—Equipment and sensors. Sensors should be selected according to the relevant failure mechanism. Vibration can be informative for certain bearing faults, while temperature or current may be useful in appropriate contexts; none replaces engineering judgment. Where equipment lacks data, sensor retrofitting may be considered. ISO 17359:2018 [6] provides general guidance on developing condition-monitoring programs for specific equipment types and objectives.

Layer 2—Connectivity and edge processing. Data acquisition devices and gateways handle transmission, time stamping, signal-quality checks, and preliminary processing. MQTT Version 5.0 [7] can be used for publish–subscribe transmission of monitoring data, whereas OPC UA [8] supports structured information exchange and interoperability among equipment, control systems, and industrial software. Protocol selection should reflect equipment compatibility, data-transfer requirements, and information security. High-frequency signals should be processed at the edge when warranted by bandwidth and latency constraints.

Layer 3—Data management and analytics. Data should be stored by machine identifier and time, alongside repair histories and load conditions. When sufficient failure data are unavailable, threshold monitoring and anomaly detection should take priority; fault classifiers or RUL estimators should be used only when suitable datasets and validation methods exist. Evaluation should track false-alarm rates, fault-detection capability, and useful warning lead time.

Layer 4—Maintenance applications and governance. Dashboards display asset health and alerts; technicians verify potential causes before issuing work orders through CMMS or suitable ERP functionality. MES information may help schedule interventions with minimal disruption to production. Safety-critical control actions must follow established procedures rather than relying solely on AI predictions.

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Equipment and monitoring signals must then be selected according to subsector characteristics. Drawing on technological features and condition-monitoring requirements, Table 6 proposes equipment categories, signals, and technical directions that could be considered in subsector-specific PdM pilots.

Table 6. Subsector-specific priorities for condition monitoring and predictive maintenance

Subsector	Candidate pilot equipment	Proposed signals	Technical orientation
Spinning	Ring-spinning machines; drive assemblies	Vibration; temperature; current	Monitor mechanical and electrical anomalies
Weaving	Looms; drive systems	Vibration; temperature; speed	Standardize measurement and data acquisition
Dyeing	Circulation pumps; motors	Vibration; temperature; pressure	Link machine signals to process conditions
Garment	Automated cutting machines; specialized equipment	Current; status; error codes	Monitor condition and link to production schedules

Source: Author's proposal based on equipment technology characteristics and condition-monitoring principles [2], [6].

Information security and operational safety are cross-cutting requirements. Expanded equipment connectivity calls for network segmentation, role-based access, access monitoring, data backups, and fail-safe arrangements during communication outages. NIST SP 800-82 Rev. 3 [9] provides guidance for assessing cybersecurity risks in operational technology systems.

2.5. IIoT–PdM implementation roadmap and evaluation criteria

Table 7. IIoT–PdM implementation roadmap and phase-transition conditions

Stage	Core tasks	Criteria for progression
1. Standardization (0–6 months)	Inventory equipment; select critical assets; standardize machine IDs, error codes, and maintenance records	Identify pilot assets, required signals, and data governance procedures
2. Condition monitoring (6–12 months)	Establish connectivity; collect data; develop operating histories; implement threshold alerts	Data meet requirements for continuity, accuracy, traceability, and safety
3. Predictive analytics (12–24 months)	Pilot models; evaluate anomaly detection; validate using independent data	Model performance meets prespecified pilot criteria
4. Integration and scaling (after 24 months)	Integrate maintenance management; assess technical and economic effects; expand deployment	Evidence demonstrates operational effectiveness, cost outcomes, and safety

Source: Author's proposal based on the analysis and synthesis of predictive maintenance research [2]–[4].

The timeframes in Table 7 are indicative planning horizons, not predictions derived from the survey. Enterprises may shorten or extend them depending on technical capacity, data quality, and technology requirements. Effectiveness assessments must establish a pre-pilot baseline covering unplanned downtime, failure frequency, maintenance costs, alert accuracy, and staff acceptance.

To enable verification, the study proposes evaluation indicators suited to each implementation stage. For data and connectivity, measures should include valid-data rates, missing-data levels, continuity, and transmission latency. For analytical models, fault-detection performance, false-alarm rates, precision, recall, and F1-score should be assessed when appropriate labeled data are available. Maintenance outcomes should be monitored through unplanned downtime, incident frequency, maintenance costs, and alert response time. Acceptance thresholds must reflect equipment characteristics and pilot objectives rather than a universal value across all subsectors. Where labeled failure-state data are unavailable, evaluation should emphasize signal stability, alert relevance, and verification by technical experts. Classification metrics such as precision, recall, and F1-score should be used only with sufficiently reliable reference data and appropriate validation methods.

Pilot assets should be selected with reference to Table 6 and the criticality assessment performed by each enterprise. Implementation options must be examined jointly in terms of data availability, safety, investment costs, and maintenance requirements. Deployment should be scaled up only when pilot findings satisfy predefined technical and economic criteria.

2.6. Discussion, contributions, and research limitations

The findings reveal uneven technology adoption across subsectors and among technologies used for data acquisition, processing, and management. In particular, sensors and mobile technologies obtained higher mean scores than cloud computing/big data and some management software systems. This reflects different trajectories of technology adoption in textile and garment enterprises and underscores the need for a systems-level assessment rather than consideration of isolated indicators.

This observation is broadly consistent with the work of Frank et al. [5], who examined alternative patterns of Industry 4.0 adoption among manufacturing firms. The present study, however, focuses on technological indicators relevant to IIoT–PdM implementation across four textile and garment subsectors. Given differences in samples and measurement instruments, the findings are compared only in terms of general trends and analytical approach, not numerical values.

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From a technical perspective, automation alone cannot serve as a sufficient measure of PdM implementation capability. Highly automated equipment still requires data accessibility, connectivity, storage, time synchronization, and links to failure information. Conversely, certain less-automated machines can be condition-monitored through appropriate sensor retrofits and data-acquisition systems.

These observations are aligned with the condition-monitoring and prognostics approach of Jardine et al. [2], in which data quality, condition diagnostics, and maintenance decisions are central. The reviews by Carvalho et al. [3] and Zonta et al. [4] likewise indicate that machine-learning applications in maintenance depend on dataset characteristics and the specific prediction task. Accordingly, the proposed architecture adopts a phased approach that prioritizes data development and condition monitoring before complex predictive models.

The study makes three contributions. First, it examines differences in automation and enabling technology adoption across four textile and garment subsectors. Second, it links the survey findings to data-acquisition, connectivity, processing, and governance requirements for IIoT–PdM. Third, it proposes a four-layer architecture, subsector-specific equipment priorities, and a staged deployment roadmap with verifiable transition conditions. These are analytical and application-oriented design contributions, not evidence of operational effectiveness in an implemented system. The added value lies not in claiming an entirely new IIoT architecture but in linking the technological features of four textile subsectors to design decisions, investment priorities, and PdM implementation conditions.

Several limitations should be acknowledged. First, the survey reflects enterprise technologies at the time of data collection and cannot directly establish conditions in later years without updated evidence. Existing indicators mainly describe technology adoption and do not directly measure IIoT interoperability, sensor-data quality, historical failures, or actual PdM performance. Furthermore, the architecture and roadmap are based on analysis and literature synthesis rather than production-line testing. Future work should select critical assets, collect operating data and incident logs, validate anomaly-detection models, and evaluate technical and economic outcomes before scaling up.

3. CONCLUSION AND RECOMMENDATIONS

3.1. Conclusions

This study assessed automation levels and technological prerequisites for IIoT connectivity in Vietnamese textile and garment enterprises using survey findings collected, processed, and synthesized by the research team. Automation varied across spinning, weaving, dyeing, and garment manufacturing, as well as between operations within individual production lines. Sensors and mobile technologies each scored 3.25/5 on average, exceeding cloud computing/big data (2.63/5), MES (2.68/5), and ERP (2.59/5). These differences indicate uneven development among technologies relevant to data acquisition, processing, and governance, but do not directly establish IIoT connectivity capability or readiness for predictive maintenance.

On the basis of these findings, the study proposes a four-layer IIoT–PdM architecture covering equipment-data acquisition, connectivity and edge processing, data management and analytics, and maintenance applications and governance. It also identifies subsector-specific monitoring equipment priorities and a four-stage implementation roadmap. The main contribution is the linkage of existing technological conditions with system design and PdM deployment requirements in smart factories. Since the architecture has not been validated with real operating data, no conclusions can yet be drawn regarding predictive performance or economic benefits.

3.2. Recommendations

Textile and garment enterprises should first assess asset criticality, access to sensor data, and existing connectivity before investing in IIoT–PdM systems. Deployment should proceed incrementally, beginning with data standardization, condition monitoring, and anomaly detection, and only subsequently developing predictive models when sufficient operational and failure-history data are available. Enterprises should also integrate maintenance information with appropriate management systems, ensure cybersecurity, and strengthen the data analytics skills of technical staff.

Research institutions and technology providers should prioritize pilot models tailored to equipment characteristics in each subsector, particularly critical assets whose failure could disrupt production. Future studies should validate the proposed architecture using real operating data, assessing connectivity quality, anomaly-detection performance, false-alarm rates, unplanned downtime, and maintenance costs. Evaluation in actual manufacturing settings will provide evidence on technical feasibility, economic effectiveness, and the conditions required to scale IIoT–PdM solutions across Vietnamese textile and garment enterprises.

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