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Artificial Intelligence Adoption in Supply Chain Management Among Vietnamese Textile and Garment Enterprises: A Digitalization Readiness Perspective

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ABSTRACT: This study examines the digitalization status of supply chain management in Vietnamese textile and garment enterprises and proposes orientations for artificial intelligence (AI) adoption based on data readiness and managerial capabilities. Using enterprise survey data covering spinning, weaving, dyeing, and garment manufacturing, the study applies descriptive statistics, comparative analysis, and a literature review to examine five supply chain management functions. The findings indicate that technology adoption scores range from 1.53 to 1.91 on a five-level scale. Furthermore, 72.04% of surveyed enterprises use basic tools for partner information management, while 62.89% rely on basic Office applications for demand forecasting. Based on the identified digitalization gaps, the study proposes a function-specific AI application matrix and a three-layer implementation framework comprising data standardization, controlled AI pilots, and supply chain integration. The findings provide a practical reference for selecting AI applications according to enterprise readiness.

KEYWORDS: artificial intelligence, supply chain management, Vietnamese textile and garment industry, digitalization, data readiness.

1. INTRODUCTION

The Vietnamese textile and garment industry comprises enterprises operating across successive stages, from spinning, weaving, dyeing and finishing to garment manufacturing and product distribution. The sequential nature of production, the involvement of numerous suppliers, and the need to fulfill domestic and international orders create growing demands for information coordination among enterprises. In the context of digital transformation, supply chain management capabilities depend not only on production equipment but also on the collection, standardization, sharing, and use of data for coordination, forecasting, and decision-making.

In supply chain management, digitalization extends beyond the use of accounting or office software. A digital supply chain requires data on orders, suppliers, materials, production schedules, inventories, and deliveries to be standardized, shared under appropriate access permissions, and used for operational coordination [1]. Research on Supply Chain Management 4.0 emphasizes the interconnection of technology, processes, and managerial capabilities [2]. AI further enables forecasting, anomaly detection, risk scoring, and recommendations for resource allocation [3]. However, deploying AI on fragmented datasets with inconsistent updates can generate misleading results and hinder implementation at an operational scale.

Previous studies have established the potential of AI for demand forecasting, inventory management, supplier evaluation, and supply chain risk control [3–5]. Nevertheless, suitable AI applications must be selected in relation to the degree of digitalization and the data conditions of individual functions. For Vietnamese textile and garment enterprises, the issue is not merely to identify which activities AI could support, but also to clarify existing data gaps, connectivity constraints, and practical implementation conditions. Accordingly, this study aims to: (i) assess technology adoption in five supply chain management functions; (ii) identify digitalization limitations and prerequisites for AI adoption; and (iii) develop a function-specific AI application matrix and a three-layer framework linked to a three-stage roadmap. Its contribution lies in relating observed digitalization gaps to AI application choices based on enterprise readiness, rather than advocating uniform technology deployment.

2. RESEARCH CONTENT

2.1. Theoretical foundations and research methodology

2.1.1. Digital supply chains and the role of AI

The textile and garment supply chain encompasses physical flows from raw materials to yarn, fabric, dyeing and finishing, garment production, and distribution, together with the information and financial flows connecting its participants. Supply chain management coordinates procurement, purchasing, production, inventory, distribution, and customer interactions. Büyüközkan and Göçer [1] argue that the transition to digital supply chains is not simply the computerization of documents; it also changes the ways in which activities are coordinated and information-based decisions are made. Zekhnini et al. [2] systematize the technological components and managerial roadmaps of Supply Chain Management 4.0.

AI can learn from historical data to support demand forecasting, late-delivery prediction, inventory anomaly detection, customer information classification, and supply optimization. Min [4] identifies foundational AI applications in SCM, while Toorajipour et al. [3] review relevant AI application areas and techniques. Demand forecasting in the textile and garment sector is particularly challenging owing to seasonality,

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design changes, product life cycles, and fluctuating orders. The review by Swaminathan and Venkitasubramony [6] highlights the potential of AI-based forecasting alongside conventional statistical methods. As AI cannot substitute for reliable data, this study regards digitalization as a foundational layer for AI adoption.

2.1.2. Research methodology

This study combines an enterprise survey, descriptive statistics, comparative analysis, and synthesis of scientific literature to assess digitalization and propose directions for AI adoption in supply chain management among Vietnamese textile and garment enterprises.

Data collection: The study surveyed 240 enterprises operating in four major segments of Vietnam's textile and garment supply chain, comprising 60 spinning enterprises, 50 weaving enterprises, 50 dyeing enterprises, and 80 garment manufacturing enterprises. The survey sample was selected using purposive sampling in geographical areas with a high concentration of textile and garment production activities to ensure the representation of enterprises across the major stages of the supply chain. The survey respondents were enterprise managers or personnel responsible for production, planning, procurement, inventory management, and supply chain management. A total of 240 questionnaires were distributed, of which 220 were returned, and 210 valid responses were retained for analysis. The indicators were aggregated for each industry segment and the overall sample. In addition, the number of valid responses was determined separately for each indicator to ensure the accuracy of the reported percentages and mean scores. Item-level valid responses for the technology adoption and Industry 4.0 readiness indicators ranged from 184 to 198; the corresponding number of valid responses (n) is reported with each table and in the text.

Survey content: The questionnaire addresses market structure, supply chain organization, and technology adoption across five functions: customer and supplier information management, partner communication, sales and order tracking, demand forecasting, and warehouse management. It also considers indicators of technological capacity, human resources, and readiness for Industry 4.0. Technology adoption is assessed on a five-level scale using criteria specific to each function. The Industry 4.0 readiness index follows the indicators and aggregation procedure of the survey.

Data analysis: Survey responses are checked, classified, and aggregated using Microsoft Excel. Descriptive statistics are used to calculate the shares of enterprises at each technology adoption level and mean scores for individual functions. Comparative analysis identifies differences across the four segments and limitations in data management, information connectivity, and readiness to adopt digital technologies.

Development of AI application orientations: A synthesis of scientific literature is combined with a qualitative comparison between the observed state of digitalization and the requirements for AI applications in each function [3–5, 7–9]. Proposed solutions are assessed against three criteria: operational necessity, data readiness, and implementation feasibility. On this basis, the study develops a matrix covering five functions and a three-layer implementation framework associated with three stages: data standardization, controlled AI piloting, and supply chain integration. The proposed framework is conceptual and has not yet been empirically validated in enterprises.

2.2. Results and discussion

2.2.1. Market characteristics and supply chain organization

The enterprise survey findings indicate differences in market structure across textile and garment segments. Exports account for 71.52% of the spinning segment and 94.95% of garment manufacturing, whereas the weaving segment records 44.77% for the domestic market and 36.92% for internal enterprise supply chains. These characteristics imply varying levels of exposure to international customers and differing needs for standardized partner data exchange across production stages. Cut–make–trim (CMT) and original equipment manufacturing/free-on-board (OEM/FOB) arrangements remain common among many enterprises, limiting their involvement in design, marketing, and relationships with end customers. Limited access to direct market data restricts the development of comprehensive forecasting datasets and increases dependence on buyers' order schedules.

From a supply chain perspective, uneven digitalization across links makes it difficult for enterprises to create a unified view from demand signals to material planning and delivery progress. Automating an individual machine or production stage is insufficient for digital SCM if orders are still updated manually by email, material records are stored in disconnected spreadsheets, and partner information lacks shared identifiers. Kache and Seuring [7] similarly emphasize challenges related to data quality, accessibility, and utilization in supply chain analytics.

Table 1. Market structure of textile and garment enterprises

Industry segment	Export market (%)	Domestic market (%)	Internal supply chain (%)
Spinning	71.52	17.56	10.92
Weaving	18.31	44.77	36.92
Dyeing	37.35	49.41	13.24
Garment manufacturing	94.95	5.05	—
Average	55.53	29.20	15.27

Source: Enterprise survey results, 2024.

2.2.2. Digitalization levels across supply chain management functions

The five-level scores obtained from the 2024 survey indicate low technology adoption in all five SCM functions. The overall mean scores are 1.70/5 for customer and supplier information management, 1.86/5 for customer communication, 1.71/5 for sales methods, 1.53/5 for demand forecasting, and 1.91/5 for raw-material and finished-goods warehouse management. Demand forecasting records the lowest score despite its central role in material planning, capacity allocation, and production scheduling. Warehouse management has the highest mean score among

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the five functions (1.91/5), yet this level still indicates limitations in technology adoption and a need to improve the timeliness, connectivity, and use of inventory data for supply chain coordination.

Across segments, dyeing records a demand forecasting score of 1.16/5 and a warehouse management score of 1.37/5, lower than those of the other groups. Garment manufacturing scores 2.06/5 for sales and 2.19/5 for communication; although relatively higher, these values do not establish integrated digitalization. The findings suggest that technology use in many enterprises remains confined to disconnected tools without data integration across functions. Differences in technology adoption across the four segments and five SCM functions are presented in Figure 1.

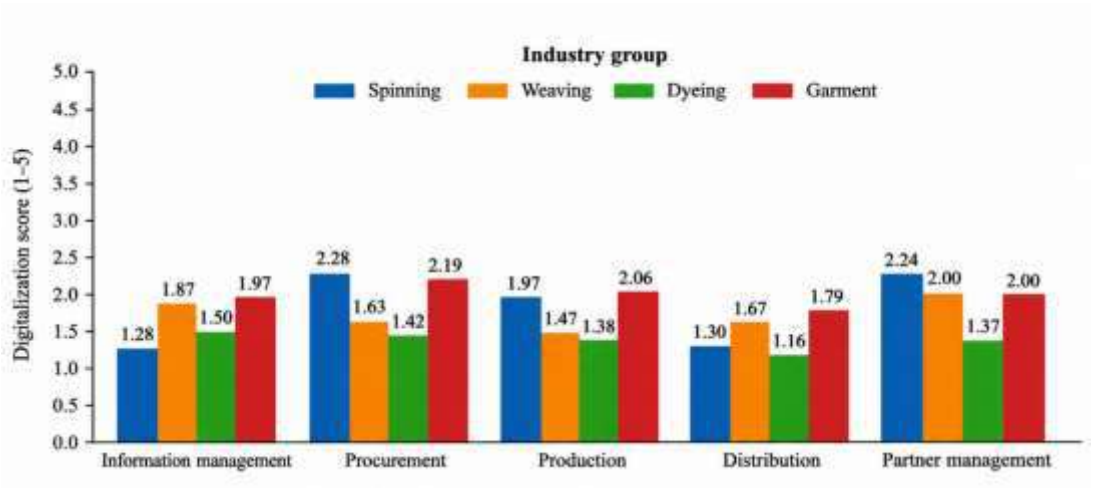


Figure 1. Digitalization scores for five supply chain management functions across four industry segments in 2024
Source: Enterprise survey results, 2024.

Figure 1 illustrates the uneven adoption of technology across segments. Dyeing scores poorly in most functions, particularly demand forecasting and warehouse management. Spinning performs relatively better in communication and inventory management, while garment manufacturing stands out in partner information management and sales. These differences suggest that enterprises should prioritize data upgrades and AI applications according to functional needs rather than applying a single solution across the entire supply chain.

2.2.3. Customer and supplier data and information exchange

Customer and supplier data provide the basis for identifying order histories, material lead times, supply quality, substitute-material availability, and commercial terms. According to the 2024 survey (n = 186), 72.04% of enterprises manage partner information using basic tools, 21.51% use professional software, and only 6.45% use specialized ERP software integrated with Industry 4.0 technologies under the survey classification. In garment manufacturing (n = 66), 63.64% use basic tools and 12.12% are at the highest integration level; the corresponding figures for spinning (n = 56) are 82.14% and 0.00%. These differences indicate that industry-wide data integration cannot be assumed.

For communication (n = 198), 38.38% of enterprises rely on in-person interaction, telephone, and email; 33.33% additionally have static websites; 22.22% operate interactive websites; and 6.06% use automated ordering software. The 2024 survey recorded no enterprises using AI or robots for communication. This does not establish that the same situation persists today, but it illustrates the earlier starting point of digital transformation, characterized by fragmented manual transactions rather than integrated transaction systems.

For AI adoption, the immediate priority is to establish standardized partner directories and harmonize customer and supplier codes, delivery lead-time fields, on-time delivery rates, quality defect records, order-change histories, and confidentiality rules. Once these data foundations are in place, supplier risk classification, delayed-delivery alerts, and document retrieval assistants become more feasible. AI assistants can help summarize emails and contracts and extract relevant information; nevertheless, contractual approval and purchasing commitments must remain the responsibility of authorized personnel.

Table 2. Digitalization levels in partner information management

Industry segment	Basic tools (%)	Professional software (%)	Industry 4.0-integrated ERP (%)
Spinning (n = 56)	82.14	17.86	0.00
Weaving (n = 28)	64.29	28.57	7.14
Dyeing (n = 36)	77.78	16.67	5.56
Garment manufacturing (n = 66)	63.64	24.24	12.12
Entire industry (n = 186)	72.04	21.51	6.45

Source: Enterprise survey results, 2024 (n = 186).

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2.2.4. Sales, order tracking, and demand forecasting

In the 2024 survey (n = 198), 41.41% of enterprises engage in direct selling, 39.39% operate at the informational e-commerce level, 16.16% at the transactional e-commerce level, and 3.03% additionally provide order journey tracking. None of the surveyed enterprises reached the highest level of integrated commerce under the author's measurement scale. Dyeing enterprises (n = 38) are concentrated in direct selling (63.16%) and informational e-commerce (36.84%). Among garment enterprises (n = 72), 30.56% have reached transactional e-commerce and 8.33% offer order journey tracking. These findings underscore limitations in order-progress visibility among customers, enterprises, and suppliers.

In demand forecasting (n = 194), 62.89% of enterprises rely on basic Office tools for data collection and processing; 24.74% use basic software; 7.22% use professional software; 4.12% rely on third-party market research; and 1.03% use Industry 4.0/AI technologies to analyze consumer behavior. Thus, although AI appears among the survey categories, its prevalence was very limited in 2024. For enterprises primarily working under subcontracting arrangements, forecasting final consumer demand is not necessarily the first priority. A more appropriate starting point may be predicting changes in demand by customer, product code, and season, as well as the probability of delivery schedule revisions. AI-driven forecasting should therefore draw on data that enterprises actually possess and can regularly update, rather than prioritizing complex models before adequate data foundations are available.

AI applications can be implemented at two levels. The first involves short-term predictions of order quantities, material arrival dates, and delayed-delivery risks, with AI performance compared against simple baselines such as moving averages, seasonal forecasts, or existing forecasting procedures. The second links forecasts to adjustments in procurement plans and capacity allocation. Waller and Fawcett [8] and Choi et al. [9] indicate that predictive analytics generates operational value when its outputs inform decisions rather than merely populating reports. To avoid misleading assessments, forecasting errors, on-time delivery rates, and the frequency of plan revisions should be monitored before, during, and after piloting.

Table 3. Methods used by enterprises to forecast market demand

Forecasting method	Industry-wide share (%)
Basic Office tools	62.89
Basic software	24.74
Professional software	7.22
Third-party market research	4.12
Industry 4.0/AI for behavioral analysis	1.03

Source: Enterprise survey results, 2024 (n = 194).

2.2.5. Warehouse management, technological capabilities, and readiness

Raw-material and finished-goods warehouses connect procurement planning, production, and delivery. The author's 2024 survey records an overall warehouse management score of 1.91/5, comprising 2.24 for spinning, 2.00 for weaving, 1.37 for dyeing, and 2.03 for garment manufacturing. Low scores point to difficulties in reconciling quantities, locations, batch codes, receipts, issues, and inventory balances. Inaccurate or delayed stock movement records can cause AI-based replenishment recommendations to increase inventories of unsuitable materials. It is therefore necessary to improve inventory data quality, batch identification, and order integration before forecasting optimal stock levels.

The 2024 survey reports an overall Industry 4.0 readiness score of 2.61/5, with segment scores of 3.02 for spinning, 2.40 for weaving, 2.30 for dyeing, and 2.85 for garment manufacturing. Of the 184 enterprises responding to this indicator, 48.91% fall within the [2,3) interval, 45.65% within [3,4), 3.26% below 2, and 2.17% within [4,5]. These figures represent the author's composite survey index, not a validated measure of AI maturity. Industry 4.0 readiness is used as an indication of general technological conditions and should not be equated with AI maturity or the likelihood of successful AI model deployment.

Analysis of the survey indicators relating to technology and human resources reveals differences among enterprises in automation levels, R&D investment capacity, data analytics skills, and information security. Constraints often arise not only from the absence of algorithms but also from fragmented data sources, transition costs, and limited system operation capabilities. Accordingly, for enterprises with inadequate digitalization, upgrading data systems, standardizing workflows, and training users may provide a more important foundation than immediately purchasing sophisticated AI solutions.

2.2.6. AI application orientations based on digitalization gaps

A synthesis of the empirical context and research on AI in SCM [3–5, 10] supports five proposed application groups. First, partner information management can use tools to extract information from documents, standardize records, and alert users to delivery schedule changes. Second, customer interaction can use information assistants and request classification, with human review of legally or commercially consequential content. Third, order management can predict delivery delays using material availability and plant capacity data. Fourth, demand forecasting can focus on order and material fluctuations and seasonality in ways suited to CMT, FOB, and ODM business models. Fifth, inventory management can employ anomaly detection and recommend safety stock based on demand variation, replenishment lead times, and supply risks.

Based on the observed digitalization gaps, the study proposes selecting AI applications according to data readiness and the degree of functional integration. Enterprises primarily relying on spreadsheets and disconnected management tools should first standardize customer, supplier, product, and order records. Enterprises with management systems and relatively complete data may pilot AI for document classification, late-delivery warnings, and inventory discrepancy detection. Where purchasing, production, warehousing, and sales data are interconnected, enterprises may consider demand forecasting models, material planning optimization, and supplier coordination tools. This tiered approach reflects

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uneven technological capabilities across segments and reduces the risks of investing beyond existing readiness. Research on IoT and supply chain risk management [10–11] also provides a basis for strengthening data connectivity and collaboration.

Table 4. Proposed AI application matrix by SCM function, data requirements, and evaluation indicators

SCM function	Proposed application	Minimum data requirements	Proposed evaluation indicators
Partner information	Document extraction and record standardization; risk alerts	Partner codes; delivery history; quality; documents	Extraction accuracy; record errors
Communication	Email classification; human-reviewed query assistant	Request histories; response procedures	Processing time; correct-response rate
Orders	Late-delivery prediction; schedule-change alerts	Order codes; production stages; milestones	On-time delivery rate; true-positive alerts
Demand forecasting	Demand forecasting by product code and customer	Order histories; seasonality; cancellations/changes	MAE/WAPE versus baseline
Warehousing	Anomaly detection; inventory level suggestions	Inventory transactions; batch codes; replenishment lead times	Stock discrepancies; days of inventory; stockouts

Source: Author's proposal based on the 2024 survey and research literature.

2.2.7. Implementation framework and enabling conditions

The study proposes a three-stage roadmap in which changes to management processes precede technological expansion. Stage 1—standardization: Designate data owners; harmonize product, supplier, order, and warehouse event identifiers; assess missing, duplicate, and erroneous records; connect ERP data or an appropriately scaled data repository; and establish access control, security, and traceability rules. At this stage, enterprises must define measurable business problems rather than treating the mere presence of AI as a success indicator.

Stage 2—controlled AI piloting: Select one problem for which data are available, such as identifying orders at risk of late delivery or forecasting material demand. Establish a manual or statistical baseline and split datasets chronologically to prevent information leakage from the future; then evaluate prediction errors and operational outcomes. The system provides recommendations, but responsible personnel must approve changes to delivery schedules, purchase orders, or suppliers. Enterprises should test for performance differences across customer groups, seasons, and product categories and maintain approval logs to support decision explainability.

Stage 3—supply chain integration: Once a pilot meets predefined criteria, connect AI outputs with material procurement, production, warehousing, and delivery planning. Inter-enterprise data sharing must be governed by agreements on access rights, data quality, and responsibilities for resolving discrepancies. Deeper integration may begin with selected strategic partners instead of imposing simultaneous requirements on all suppliers. Training should combine textile and garment knowledge, SCM expertise, data skills, and AI oversight; enterprises should establish model-monitoring procedures and reassess performance when order structures change. The OECD Recommendation on trustworthy AI [12] provides a relevant reference for transparency, accountability, and risk management. Progression from data standardization to AI pilots should depend on the availability of sufficiently complete, consistent, and traceable data. Similarly, integration should be expanded only after pilots meet agreed evaluation indicators, with monitoring arrangements and clear governance responsibilities. In this way, the roadmap reflects enterprise readiness rather than a fixed deadline imposed across the entire industry.

Given the large number of small and medium-sized enterprises in the sector, a phased approach helps avoid diffuse investment. Smaller enterprises should prioritize management software with data export functionality, standardized coding systems, and automated reporting; more advanced machine-learning models should be considered only by enterprises with complex supply chains and consistent datasets. Cost-effectiveness assessments must include data cleaning, integration, retraining, maintenance, information security, and human oversight costs rather than software acquisition costs alone. Recent research on digital supply chain collaboration in the Vietnamese textile and garment industry also highlights the importance of coordination among stakeholders [13].

Drawing on the survey findings and the assessment of implementation conditions, the study proposes a three-layer AI adoption framework for SCM: digital data and data governance; function-specific AI applications; and supply chain management decisions and performance evaluation. These layers are implemented through three stages—standardization, piloting, and integration—as illustrated in Figure 2.

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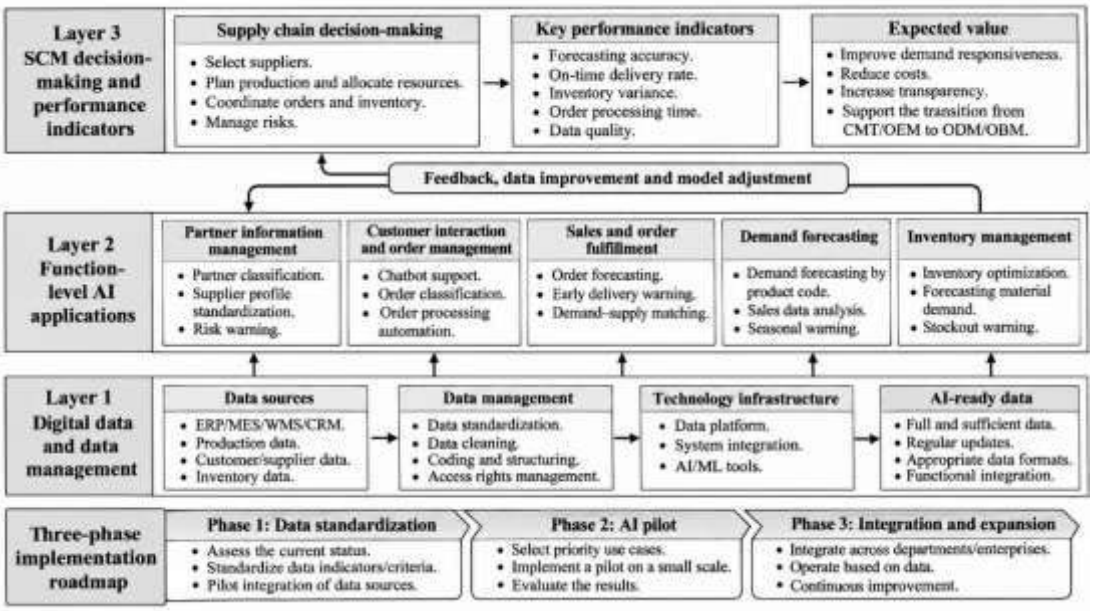


Figure 2. Three-layer framework for AI adoption in supply chain management among Vietnamese textile and garment enterprises
Source: Author's proposal based on the study findings and literature review.

Figure 2 shows the connections between data, AI applications, and decision-making in SCM. The data layer ensures that inputs are standardized and interoperable; the AI application layer supports function-specific analytics, forecasting, and warnings; and the management layer uses analytical outputs to inform decisions and assess performance against relevant indicators. Feedback from performance evaluation supports dataset updates and model refinement, establishing a continuous improvement mechanism. Implementation through three stages enables enterprises to select applications suited to their circumstances before expanding supply chain integration.

3. CONCLUSIONS AND RECOMMENDATIONS

3.1. Conclusions

The results suggest that technology adoption in SCM among Vietnamese textile and garment enterprises remains limited and uneven across industry segments. Mean scores for the five functions range from 1.53 to 1.91 on a five-level scale; demand forecasting records the lowest score (1.53/5), followed by customer and supplier information management (1.70/5). Differences among spinning, weaving, dyeing, and garment manufacturing indicate heterogeneous digital transformation needs and AI adoption conditions, calling for approaches aligned with each enterprise's operations and readiness.

Based on the analysis of digitalization status and the literature synthesis, the study proposes a function-specific AI adoption matrix and a three-layer implementation framework comprising digital data and data governance, AI applications by function, and management decisions and performance evaluation. The framework proceeds through data standardization, controlled AI piloting, and supply chain integration. The study contributes by linking digitalization gaps to AI application choices that reflect enterprise readiness.

The study is limited to analysis of survey findings and the development of a conceptual framework; it does not empirically test the effectiveness of AI models in enterprise settings. The proposals therefore require further evaluation through enterprise-based experimental research.

3.2. Recommendations

For textile and garment enterprises, priority should be given to standardizing customer, supplier, order, and inventory data and improving information connectivity between departments before adopting AI. Initial applications should target functions with relatively complete data and measurable objectives, such as late-delivery warnings, raw-material demand forecasting, and inventory discrepancy detection. Enterprises should pilot proposed solutions, evaluate their effectiveness, and control risks before expanding supply chain integration. For industry associations and digital transformation support organizations, priorities include promoting shared data standards, helping enterprises access technologies suited to their scale, and strengthening workforce training that combines SCM knowledge with data analytics and AI skills. Partnerships and information-sharing arrangements among supply chain participants should also be encouraged to enhance coordination throughout the textile and garment sector. For future research, the survey scope should be expanded, AI readiness should be evaluated across enterprise groups, and proposed solutions should be tested in practice. Quantifying impacts through forecasting accuracy, on-time delivery rates, inventory discrepancies, and processing time would help validate the feasibility and effectiveness of the proposed framework.

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