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Assessing Human Resource Capabilities, R&D Activities, And Smart Manufacturing Readiness in Vietnam's Textile and Garment Enterprises: Implications for AI Adoption

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ABSTRACT: This study assesses human resource capabilities, research and development (R&D) activities, and readiness for smart manufacturing transformation among Vietnamese textile and garment enterprises, with implications for artificial intelligence (AI) adoption. Based on a 2024 survey of 98 enterprises conducted by the research team, the study employs descriptive statistics and comparative analysis across four subsectors: spinning, weaving, dyeing, and garment manufacturing, supported by relevant scientific literature. The findings reveal limitations in data analysis and information security skills, while R&D activities are predominantly organized within existing departments. Industry 4.0 readiness also varies across subsectors. Based on these findings, the study identifies gaps in workforce capabilities, innovation organization, and technological preparedness. It proposes a phased approach to AI adoption tailored to enterprise readiness, thereby supporting the transition toward smart manufacturing in Vietnam's textile and garment industry.

KEYWORDS: human resources, research and development, smart manufacturing, Vietnam's textile and garment industry, artificial intelligence

1. INTRODUCTION

Against the backdrop of the Fourth Industrial Revolution (Industry 4.0), the transition to smart manufacturing requires comprehensive changes in manufacturing enterprises, encompassing technology, human resources, data, and managerial practices. In Vietnam's textile and garment industry, multi-stage production processes and labor-intensive operations mean that transformation depends not only on equipment automation but also on data utilization capabilities and the organization of technological innovation. Zhong et al. [1] argue that smart manufacturing requires connectivity among production systems, data, and decision-making processes. Schumacher et al. [2] likewise emphasize that Industry 4.0 readiness should be assessed across multiple dimensions, including technology, strategy, and organizational capability.

In the textile and garment industry, multiple production stages, a large share of direct labor, and differences in technological structures across spinning, weaving, dyeing, and garment manufacturing may lead to uneven levels of transformation readiness. International research identifies shortages of appropriately skilled personnel and financial resources as important barriers, particularly for small and medium-sized enterprises (SMEs) [3]. Digital transformation also entails changes in value creation and organizational arrangements [4]. Consequently, an assessment confined to equipment acquisition capacity cannot adequately capture the conditions required for AI adoption.

In response, this study simultaneously evaluates three dimensions among Vietnamese textile and garment enterprises: human resource capabilities, R&D activities, and readiness for smart manufacturing. Its contribution lies in using direct survey evidence to identify differences across subsectors while examining these three dimensions within a complementary analytical framework to determine priority conditions before AI deployment. On this basis, the study proposes directions for strengthening data capabilities, organizing R&D, and introducing AI progressively in line with enterprises' actual circumstances.

The study addresses three research questions: (i) Which skills constitute the most prominent weaknesses among textile and garment workers? (ii) How are R&D activities organized and funded? (iii) How do these gaps relate to smart manufacturing readiness and the prioritization of AI deployment?

2. RESEARCH CONTENT

2.1. Theoretical framework and research methodology

The study conceptualizes smart manufacturing readiness as a composite capability comprising three mutually supportive pillars: (1) digital human resources, (2) innovation capacity and R&D organization, and (3) organizational, technological, and governance foundations. Research into Industry 4.0 implementation patterns indicates that foundational technologies, including big data and data analytics, tend to be more difficult to deploy than frontline applications [5]. The use of machine learning in manufacturing depends on data quality, process knowledge, and the ability to interpret models [6]. The integration of physical and digital environments also provides an important foundation for smart manufacturing systems [7].

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In this article, AI refers to technologies capable of supporting forecasting, pattern recognition, anomaly detection, and decision optimization. Its implementation should be connected to process-improvement objectives and worker participation, consistent with research on Industry 4.0 roadmaps [8]. R&D is regarded as a mechanism for absorbing and adapting solutions to local conditions, rather than being equated with expenditure on equipment purchases.

Drawing on theoretical synthesis and the survey indicators, the study develops an analytical framework with three complementary pillars: human resource capabilities, R&D activities, and Industry 4.0 readiness. As illustrated in Figure 1, these pillars are considered jointly to identify gaps in skills, innovation organization, and technological conditions, thereby establishing priorities for AI implementation in textile and garment enterprises. The framework is intended as an analytical guide and does not imply statistically verified causal relationships among the pillars.

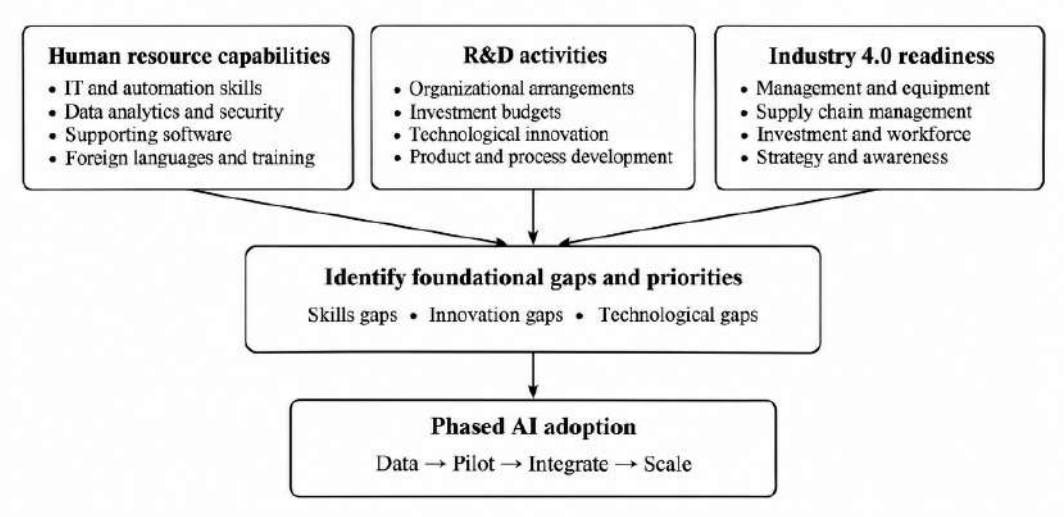


Figure 1. Analytical framework of foundational conditions for AI implementation in textile and garment enterprises
Source: Author's proposal based on the synthesis of theoretical studies and survey indicators.

2.2. Survey data and analytical methods

To operationalize this framework, the study uses survey data collected by the research team from Vietnamese textile and garment enterprises across four subsectors: spinning, weaving, dyeing, and garment manufacturing. The 2024 survey covered 98 enterprises, comprising 29 spinning firms, 15 weaving firms, 19 dyeing firms, and 35 garment firms. Purposive sampling was applied to ensure representation of subsectors with different technological and production arrangements. Questionnaires were administered to managers and personnel responsible for engineering, production, or R&D. Indicators were aggregated by subsector and for the entire sample, with the number of valid responses identified separately for each indicator to support accurate calculation of proportions and mean scores.

The survey covered three groups of indicators: (i) human resource capabilities, including information technology, automation, data analysis, information security, software utilization, and foreign-language skills; (ii) R&D activities, covering organizational structure, investment budgets, and technological innovation; and (iii) Industry 4.0 readiness, measured through management systems, machinery and equipment, supply chain management, investment and development, labor, and strategic orientation. Qualitative indicators were quantified on a five-point rating scale, with higher scores indicating higher assessments of the respective dimensions. R&D organization and budgets were reported as percentages of enterprises. Because valid response counts may differ across question groups, each indicator's proportion was calculated using its corresponding number of valid enterprise responses.

The analysis applies descriptive statistics, synthesis, and comparisons across subsectors to identify differences in workforce capabilities, R&D activities, and conditions for production transformation. Industry 4.0 readiness is assessed using component indicators and an overall score calculated according to the survey instrument's methodology. Findings are discussed in relation to relevant studies to develop AI adoption directions suited to enterprise circumstances. As statistical relationships among indicator groups were not tested, the results are interpreted descriptively and comparatively, without claims of causal effects. The Industry 4.0 readiness index is used to identify foundational conditions for smart manufacturing transformation and should not be regarded as a direct measure of AI deployment readiness.

2.3. Assessment of human resource capabilities

Human resource capabilities are assessed through six skill groups associated with enterprises' ability to access and use technologies. The survey findings reveal uneven skill assessments, particularly between general information technology competencies and specialized skills required for data exploitation. Figure 2 presents industry-wide mean ratings for the six groups, providing a basis for identifying competencies that warrant priority development during the transition to smart manufacturing.

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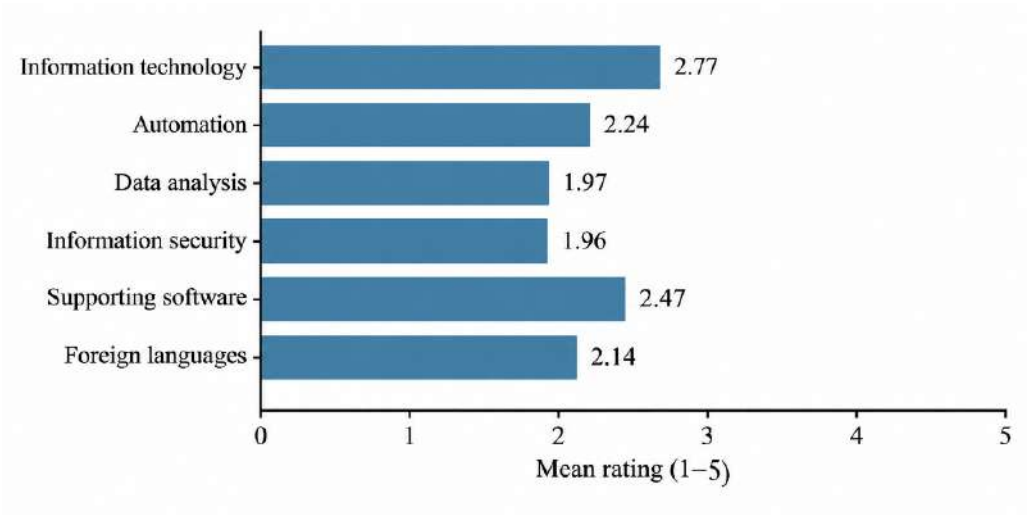


Figure 2. Mean ratings of workforce skill groups in the textile and garment industry
Source: Research team survey results, 2024.

Figure 2 indicates that information technology skills receive the highest mean score (2.77/5), followed by the use of supporting software (2.47/5), whereas data analysis (1.97/5) and information security (1.96/5) receive the lowest ratings. The gap between general IT skills and specialized data competencies underscores the need to strengthen enterprises' analytical, data-management, and data-protection capabilities. Table 1 provides a more detailed comparison of the six skill groups across spinning, weaving, dyeing, and garment manufacturing.

Table 1. Workforce skill ratings by subsector

Skill	Spinning	Weaving	Dyeing	Garment	Average
IT	3.00	2.47	2.68	2.95	2.77
Automation	2.79	2.07	1.63	2.46	2.24
Data analysis	2.59	1.53	1.21	2.56	1.97
Information security	2.79	1.13	1.21	2.72	1.96
Supporting software	2.86	2.07	1.74	3.22	2.47
Foreign languages	2.52	1.80	1.84	2.41	2.14

Source: Research team survey results, 2024. Average: unweighted mean of the four subsectors.

Table 1 highlights differences in technological capabilities across subsectors. Data analysis skills are rated relatively higher in spinning and garment manufacturing, at 2.59 and 2.56 points, respectively, compared with 1.53 in weaving and 1.21 in dyeing. Likewise, information security ratings in weaving (1.13) and dyeing (1.21) are considerably lower than those in spinning (2.79) and garment manufacturing (2.72). For supporting software skills, garment manufacturing scores 3.22, compared with 1.74 in dyeing. These differences suggest that digital skills development should reflect subsector-specific characteristics rather than follow a uniform training program. In particular, improving data analysis and information security skills should be prioritized when preparing for AI applications in manufacturing.

Beyond existing skill levels, training practices also indicate enterprises' capacity to develop personnel for technological transformation. The training structure remains unbalanced: internal training scores 3.64/5 on average, while hiring external experts to deliver in-house training scores 2.40, sending employees to domestic training programs 2.56, and overseas training 2.00. These results suggest substantial reliance on internal training, with relatively limited access to specialized expertise and technological exchange. The OECD [9] emphasizes upskilling and reskilling during digital transformation, particularly continuous learning and the capacity to work alongside emerging technologies.

The survey of Industry 4.0 adoption barriers assigns ratings of 4.33/5 to shortages of suitable personnel and 4.02/5 to insufficient knowledge, compared with 3.03/5 for excessive technological complexity. Among external barriers, shortages of trained personnel and experts score 4.67/5 and 4.34/5, respectively. Although these measures belong to different indicator groups, they collectively suggest the importance of human resources in technological adoption. These findings align with Horváth and Szabó [3], who emphasize workforce-related factors in Industry 4.0 transformation. Müller et al. [10] likewise indicate that organizational challenges, fit with production activities, and enterprise characteristics should be considered when assessing implementation conditions.

2.4. Assessment of R&D activities

The survey indicates that R&D activities in textile and garment enterprises are mainly embedded in existing functional departments rather than conducted by separate research units. Specifically, 12.24% of surveyed enterprises have no R&D unit, 68.37% integrate R&D into other departments, and 19.39% maintain independent R&D departments. These descriptive figures capture organizational arrangements rather than research quality, product-development capabilities, or commercialization performance. It would therefore be inappropriate to conclude that all enterprises with embedded R&D perform poorly; nevertheless, this arrangement may complicate the assignment of responsibilities for data governance and continuous AI experimentation. Table 2 reports the results by subsector.

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Table 2. Organizational structure of R&D activities by subsector

Subsector	No R&D (%)	Embedded R&D (%)	Independent R&D (%)
Spinning	0.00	93.10	6.90
Weaving	20.00	66.67	13.33
Dyeing	10.53	63.16	26.32
Garment	20.00	51.43	28.57
Overall	12.24	68.37	19.39

Source: Research team survey results, 2024 (n = 98).

As shown in Table 2, embedded or part-time R&D is the predominant arrangement among surveyed enterprises (68.37%), while 19.39% have independent R&D departments and 12.24% have no R&D department. By subsector, spinning has the highest proportion of embedded R&D (93.10%), whereas garment manufacturing has the highest proportion of independent R&D units (28.57%). These findings reflect different approaches to organizing research and technological innovation. However, organizational form does not directly indicate R&D quality or effectiveness; investment resources must also be considered when assessing innovation capacity.

In addition to organizational arrangements, budget allocation indicates the financial resources devoted to R&D. The study examines annual R&D budgets as a proportion of pre-tax profits, grouped by level of expenditure. Table 3 presents the distribution of enterprises across these budget categories and subsectors.

Table 3. Distribution of enterprises by R&D budget as a proportion of pre-tax profit

Subsector	0%	Below 1%	1–3%	3–5%	Above 5%
Spinning	0.00	58.62	31.03	10.34	0.00
Weaving	6.67	46.67	46.67	0.00	0.00
Dyeing	52.63	31.58	15.79	0.00	0.00
Garment	13.33	46.67	23.33	0.00	16.67
Overall	16.13	47.31	27.96	3.23	5.38

Source: Research team survey results, 2024 (n = 93; garment n = 30).

Table 3 indicates that most surveyed enterprises allocate relatively limited financial resources to R&D. Across the sample, 16.13% report no annual R&D budget, while 47.31% allocate less than 1% of pre-tax profit to R&D. Together, these groups account for 63.44% of the 93 enterprises that responded to this indicator. Dyeing has the highest proportion of enterprises with no R&D budget (52.63%), whereas no spinning enterprise falls into this category. These differences indicate uneven R&D funding capacity across subsectors. Nevertheless, R&D expenditure relative to pre-tax profit should not be confused with R&D expenditure relative to revenue, and does not directly measure the effectiveness of budget use. For AI adoption, the findings suggest selecting pilots that match enterprises' financial resources and organizational capabilities.

Dalenogare et al. [11] show that the expected contributions of Industry 4.0 technologies to industrial performance vary by technology group and performance dimension. Accordingly, AI solutions should be selected against specific improvement objectives and the ability to evaluate implementation outcomes, rather than on the basis of technology investment plans alone.

2.5. Industry 4.0 readiness: The gap between strategy and current conditions

Industry 4.0 readiness is evaluated to identify the foundational conditions for smart manufacturing transformation in Vietnam's textile and garment enterprises. The analysis compares spinning, weaving, dyeing, and garment manufacturing, while examining management, machinery and equipment, supply chain management, investment and development, labor, and strategic orientation. Figure 3 compares readiness levels across the four subsectors.

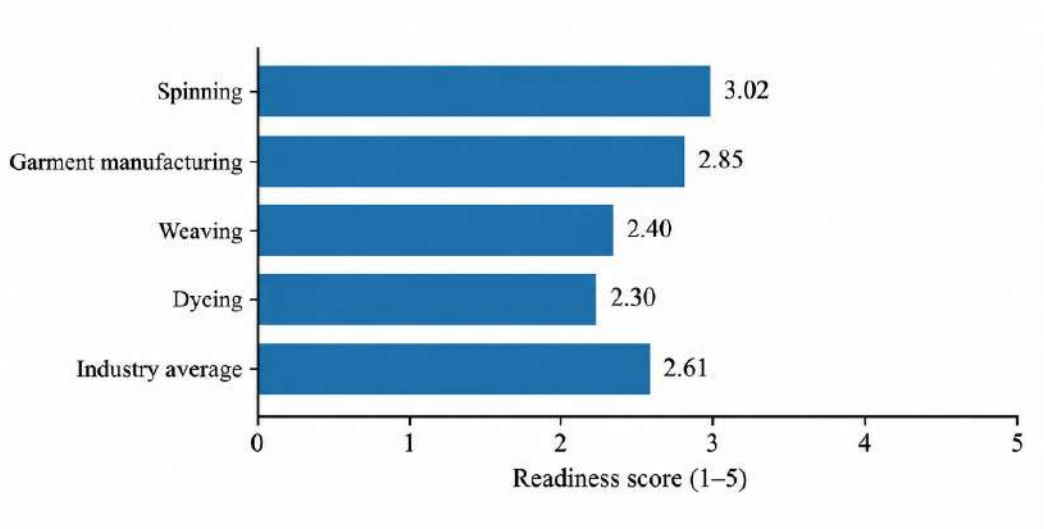


Figure 3. Industry 4.0 readiness by subsector in 2024
Source: Research team survey results, 2024.

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Figure 3 shows that average Industry 4.0 readiness across the surveyed industry is 2.61/5. Spinning records the highest score (3.02), followed by garment manufacturing (2.85), weaving (2.40), and dyeing (2.30). The 0.72-point gap between the highest- and lowest-rated subsectors illustrates unequal foundational conditions for smart manufacturing transformation. This suggests that subsectors require technology adoption roadmaps aligned with their existing readiness levels. Table 4 presents industry-wide component scores to further identify limitations in enterprise transformation conditions.

Table 4. Components of the Industry 4.0 readiness index

Component	Score
Management systems (B1)	2.82
Machinery and equipment (B2)	2.18
Supply chain management (B3)	1.93
Investment and development (B4)	2.53
Labor (B5)	3.02
Current implementation assessment (B)	2.22
Industry 4.0 awareness and strategy (C)	2.84
Overall readiness	2.61

Source: Research team survey results, 2024.

Table 4 reveals variation among Industry 4.0 readiness components. Labor has the highest score (3.02), followed by management systems (2.82), whereas machinery and equipment score 2.18 and supply chain management ranks lowest at 1.93. Notably, Industry 4.0 awareness and strategy score 2.84, exceeding the assessment of current implementation conditions (2.22). This suggests a gap between strategic orientation and operational realities. The findings indicate that awareness and strategic planning need to be accompanied by improvements in data governance, equipment connectivity, and supply chain coordination when selecting AI solutions for production activities.

Regarding the distribution of readiness scores (n = 92), 48.91% of surveyed enterprises fall between 2 and below 3 points, 45.65% between 3 and below 4, 3.26% below 2, and only 2.17% between 4 and 5. Given the very small share in the highest category, immediate industry-wide deployment of AI would not be appropriate for the readiness conditions observed at the time of the survey. Industry 4.0 maturity models and readiness assessment frameworks emphasize that implementation must reflect enterprises' actual capability levels [2, 12].

2.6. Identified gaps and implications for AI adoption

Taken together, the findings indicate that textile and garment enterprises' transition to smart manufacturing must consider workforce capabilities, R&D activities, and organizational and technological conditions simultaneously. Weaknesses in data analysis and information security constrain preparation of data for AI applications; the prevalence of embedded R&D calls for suitable arrangements for experimentation and technology absorption; and divergent readiness levels across subsectors imply that application problems should be selected according to specific circumstances. Research on machine learning in manufacturing [6] and cyber-physical systems [7] provides a theoretical basis for integrating data and technology in this process.

An important implication is that AI adoption should not be equated with labor replacement. Given limited data analysis capabilities, enterprises should initially favor decision-support applications whose outputs remain subject to expert oversight, while safeguarding workers' interests. The ILO's report on the future of work in textiles, clothing, leather, and footwear stresses that technological change should be associated with skills development and sustainable employment [13].

Based on the findings on workforce capabilities, R&D activities, and Industry 4.0 readiness, the study proposes a phased AI implementation roadmap tailored to textile and garment enterprises. The roadmap comprises four stages: standardizing data and foundational capabilities, piloting applications, integrating AI into production, and scaling successful solutions. Table 5 summarizes the central activities and corresponding evaluation criteria.

Table 5. Proposed phased AI implementation roadmap based on enterprise readiness

Stage	Key conditions and activities	Expected outcomes
1. Standardization	Inventory data; assign data ownership; code defects; standardize procedures; train staff in IT, analytics, and information security.	Establish traceable data; KPIs: data completeness, entry errors, and share of labeled samples.
2. Pilot	Create a cross-functional R&D team; select one workshop; assess data quality; use a control group or before–after comparisons.	Computer-vision defect detection, demand forecasting, predictive maintenance; KPIs: accuracy, false alarms, downtime, and cost.
3. Integration	Connect AI outputs to MES/ERP and approval processes; monitor data/model drift, security, and accountability.	Measure changes in productivity, quality, and delivery lead time; calculate ROI from actual data.
4. Scaling	Review effectiveness, standardize knowledge, retrain personnel, and extend implementation to other processes/plants when thresholds are met.	Compare performance by subsector, maturity level, and enterprise size.

Source: Author's proposal based on survey results and theoretical synthesis [5–8, 14].

Table 5 indicates that AI implementation should progress from establishing foundational conditions to testing and subsequently scaling applications. Data standardization and workforce development constitute the initial priorities, especially for enterprises with limited readiness.

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Pilots should target specific production problems and apply explicit performance criteria before integration into management systems and wider rollout. Appropriate applications may differ across subsectors: garment manufacturing may prioritize visual defect inspection or production schedule forecasting; spinning may focus on equipment monitoring and predictive maintenance; weaving may emphasize fabric defect detection; and dyeing may first standardize recipe and process data before testing optimization solutions. These are proposed application directions derived from the study's findings and theoretical review, not AI implementation outcomes empirically verified at the surveyed enterprises.

From a governance perspective, each pilot should designate an operations lead, a data steward, R&D personnel, and a worker representative. Success criteria should be defined in advance, including baseline indicators, testing scope, implementation costs, product-quality impacts, and stop rules for underperforming models. Industry 4.0 implementation research suggests that the interaction between technological innovation and production management practices should be taken into account [15].

2.7. Research contributions and limitations

The study provides empirical evidence on workforce capabilities, R&D activities, and Industry 4.0 readiness among Vietnamese textile and garment enterprises. By jointly examining these three dimensions, it identifies prominent gaps in data skills, innovation organization, and technological conditions, while clarifying cross-subsector differences. Its applied contribution is a phased AI adoption approach that prioritizes human capital development, experimental arrangements, and data foundations before scaling solutions.

Because the study draws on a survey conducted in 2024, its findings describe only the sampled enterprises at that point in time and cannot be directly extrapolated to AI deployment readiness in 2026. Moreover, the analysis relies on descriptive statistics and comparisons of aggregated indicators, without testing causal relationships among workforce capabilities, R&D activities, and readiness levels. Future research should expand the dataset, introduce AI governance indicators, and experimentally assess the effectiveness of implemented AI solutions.

3. CONCLUSION AND RECOMMENDATIONS

3.1. Conclusions

The findings reveal limitations and cross-subsector differences in workforce capabilities, R&D activities, and Industry 4.0 readiness among Vietnamese textile and garment enterprises. Data analysis and information security skills score 1.97 and 1.96 out of five, respectively; 68.37% of enterprises organize R&D as an embedded activity; and industry-wide Industry 4.0 readiness averages 2.61/5. Spinning records the highest readiness score (3.02), while dyeing records the lowest (2.30). These findings demonstrate uneven data capabilities, innovation organization, and technological conditions, and underscore the need to consider all three dimensions when assessing the foundations for smart manufacturing transformation. The study thereby offers practical evidence for identifying AI deployment priorities appropriate to enterprise readiness rather than prescribing a uniform industry-wide roadmap.

3.2. Recommendations

Textile and garment enterprises should prioritize improvements in workers' data analysis, information security, and technology utilization skills, while strengthening R&D through coordination among engineering, production, and management functions. AI should be introduced through a progression from data standardization and the selection of pilot problems to performance assessment and scaling. Applications should address real operational needs, have measurable performance indicators, and match each enterprise's readiness level.

Educational institutions, industry associations, and regulatory agencies should strengthen collaboration on digital skills training, facilitate enterprises' access to specialists, and develop applied research capabilities. Digital transformation support programs should address human resources, innovation organization, and data infrastructure together, rather than focusing solely on equipment investment. Further surveys and experimental evaluations are needed to establish the effectiveness of AI applications across individual textile and garment subsectors.

REFERENCES

1) Zhong, R.Y., Xu, X., Klotz, E., Newman, S.T., 2017. Intelligent Manufacturing in the Context of Industry 4.0: A Review. Engineering, 3(5), 616–630. DOI: 10.1016/j.eng.2017.05.015.
2) Schumacher, A., Erol, S., Sihn, W., 2016. A Maturity Model for Assessing Industry 4.0 Readiness and Maturity of Manufacturing Enterprises. Procedia CIRP, 52, 161–166. DOI: 10.1016/j.procir.2016.07.040.
3) Horváth, D., Szabó, R.Zs., 2019. Driving forces and barriers of Industry 4.0: Do multinational and small and medium-sized companies have equal opportunities? Technological Forecasting and Social Change, 146, 119–132. DOI: 10.1016/j.techfore.2019.05.021.
4) Vial, G., 2019. Understanding digital transformation: A review and a research agenda. The Journal of Strategic Information Systems, 28(2), 118–144. DOI: 10.1016/j.jsis.2019.01.003.
5) Frank, A.G., Dalenogare, L.S., Ayala, N.F., 2019. Industry 4.0 technologies: Implementation patterns in manufacturing companies. International Journal of Production Economics, 210, 15–26. DOI: 10.1016/j.ijpe.2019.01.004.
6) Wuest, T., Weimer, D., Irgens, C., Thoben, K.-D., 2016. Machine learning in manufacturing: advantages, challenges, and applications. Production & Manufacturing Research, 4(1), 23–45. DOI: 10.1080/21693277.2016.1192517.
7) Lee, J., Bagheri, B., Kao, H.-A., 2015. A Cyber-Physical Systems architecture for Industry 4.0-based manufacturing systems. Manufacturing Letters, 3, 18–23. DOI: 10.1016/j.mfglet.2014.12.001.
8) Ghobakhloo, M., 2018. The future of manufacturing industry: a strategic roadmap toward Industry 4.0. Journal of Manufacturing Technology Management, 29(6), 910–936. DOI: 10.1108/JMTM-02-2018-0057.
9) OECD, 2023. OECD Skills Outlook 2023: Skills for a Resilient Green and Digital Transition. OECD Publishing, Paris. DOI: 10.1787/27452f29-en.
10) Müller, J.M., Kiel, D., Voigt, K.-I., 2018. What Drives the Implementation of Industry 4.0? The Role of Opportunities and Challenges in the Context of Sustainability. Sustainability, 10(1), Article 247. DOI: 10.3390/su10010247.

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11) Dalenogare, L.S., Benitez, G.B., Ayala, N.F., Frank, A.G., 2018. The expected contribution of Industry 4.0 technologies for industrial performance. International Journal of Production Economics, 204, 383–394. DOI: 10.1016/j.ijpe.2018.08.019.
12) Lichtblau, K., Stich, V., Bertenrath, R., Blum, M., Bleider, M., Millack, A., Schmitt, K., Schmitz, E., Schröter, M., 2015. Industrie 4.0 Readiness. Impuls-Stiftung, Frankfurt. https://impuls-stiftung.de/wp-content/uploads/2022/05/Industrie-4.0-Readiness-english.pdf.
13) International Labour Organization (ILO), 2019. The future of work in textiles, clothing, leather and footwear. ILO, Geneva. https://www.ilo.org/sector/Resources/publications/WCMS_669355/lang--en/index.htm.
14) Lasi, H., Fettke, P., Kemper, H.-G., Feld, T., Hoffmann, M., 2014. Industry 4.0. Business & Information Systems Engineering, 6(4), 239–242. DOI: 10.1007/s12599-014-0334-4.
15) Tortorella, G.L., Fettermann, D., 2018. Implementation of Industry 4.0 and lean production in Brazilian manufacturing companies. International Journal of Production Research, 56(8), 2975–2987. DOI: 10.1080/00207543.2017.1391420.

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