Available on: https://jefrr.ep-journals.org/ E-ISSN: 3051-3650, P-ISSN: 3051-3642

Journal of Economic Finance Research and Review

Volume: 02 Issue: 11 November 2026

An Integrated Framework for Artificial Intelligence and Smart Technologies in Vietnamese Garment Production Management

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Published Date: November 24, 2026 **Article DOI: 10.65150/EP-jefrr/V2E11/2026-09**

ABSTRACT: This study examines the potential application of artificial intelligence (AI) and smart technologies in production process innovation to support productivity improvement in Vietnam's garment industry. Using a literature review combined with comparative analysis and thematic synthesis, the study examines technology applications in design, material preparation, production line organization, quality control, and energy management. The findings indicate that digitalization, automation, and production management improvements provide a foundation for AI integration, although their benefits must be distinguished from the direct effects of AI. Accordingly, the study proposes a four-layer integration framework linking production data, connectivity infrastructure, AI-based analysis, and management decisions. It also identifies potential AI intervention points and corresponding performance indicators. The proposed framework provides a reference for garment enterprises in Vietnam when planning AI adoption and requires empirical validation to establish its actual contribution to productivity improvement.

KEYWORDS: Artificial intelligence, Smart technologies, Production process innovation, Labor productivity, Vietnam's garment industry.

1. INTRODUCTION

Vietnam's garment industry makes a major contribution to industrial development, employment, and national exports. According to the Viet Nam Textile and Apparel Association (VITAS), textile and garment export turnover reached approximately USD 46.2 billion in 2025, nearly 6% higher than in the previous year [1]. Nevertheless, the industry faces international competition, fluctuating labour, material and energy costs, and increasingly stringent requirements concerning quality, delivery schedules and sustainability. The International Labour Organization (ILO) emphasizes the need for value-chain upgrading, skills development and technological innovation to sustain competitiveness [2]. Improving production processes to raise productivity and resource-use efficiency is therefore an important priority for Vietnamese garment manufacturers. Advances in artificial intelligence (AI) and smart technologies offer new approaches to organizing, managing and operating production. Three-dimensional design and simulation, industrial robots, sensors, radio-frequency identification (RFID), and manufacturing management systems are being applied at various stages of garment production. Studies of applications in China and at GUIMA in Portugal demonstrate the potential of these technologies for sample development, planning, data acquisition and production monitoring [3], [4]. Unlike conventional automation, which mainly executes predetermined operations, AI can analyse data, identify patterns, generate forecasts and support the optimization of managerial decisions. Integrating AI with smart technologies may therefore enhance operational flexibility and performance. Previous studies have reported improvements associated with equipment automation, production-line organization, shorter changeover times and energy management [5]–[9]. Such findings, however, generally relate to individual technologies or organizational interventions under specific circumstances. Within the literature reviewed, links between shop-floor data, AI analytical and predictive functions, managerial decisions and productivity indicators have not been examined in a unified framework tailored to garment production. Moreover, the effects of AI must be distinguished from those attributable to digitization, automation and organizational improvement. This gap motivates an integrated approach connecting production data, analytical technologies and management decisions.

Accordingly, this study has three objectives: (i) to synthesize evidence concerning AI, smart technologies and production process innovation in garment manufacturing; (ii) to identify potential AI intervention points, data requirements and decision-support mechanisms across production stages; and (iii) to propose an integrated framework and relevant indicators for evaluating potential implementation effects in Vietnamese garment enterprises. Its contribution is to link production operations, data, AI functions and managerial decisions in a coherent conceptual structure. The framework is intended to guide further investigation and requires empirical validation before productivity gains can be attributed to AI.

2. RESEARCH CONTENT

2.1. Theoretical foundations of AI, smart technologies and production process innovation

Artificial intelligence refers to computational systems capable of performing functions such as recognition, data analysis, prediction and decision support. Under the OECD definition [10], an AI system infers from input information how to generate outputs such as predictions, content, recommendations or decisions, with varying degrees of autonomy. In industrial production, AI may be applied to equipment-condition analysis,

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demand forecasting, anomaly detection and operational optimization. For garment enterprises, data from product design, orders, sewing lines and quality control may provide a basis for improving decision accuracy, flexibility and production management.

Smart manufacturing technologies encompass connected equipment, sensors, robotics, identification systems and data-management platforms that capture, communicate and process operating information. RFID, automated guided vehicles (AGVs), sewing robots, intelligent overhead conveyor systems and production-management software are used at different stages of garment manufacturing. These technologies should not automatically be classified as AI: many primarily enable digitization, automation and the generation of data that may subsequently be used by AI-enabled analytical applications.

According to the OECD/Eurostat Oslo Manual [11], process innovation involves introducing a new or significantly improved process compared with an organization's previous practice. In garment production, examples include digital garment design and simulation, automated cutting, improved line organization, real-time monitoring and more efficient use of materials. Integrating AI with smart technologies may support a transition from experience-based management toward decisions informed by operational data and systematic analysis.

This paper conceptualizes labour productivity in relation to conforming output and the quantity of labour or working time used. At sewing-line level, the number of conforming garments per labour-hour provides a direct productivity measure. Line efficiency, style-changeover time, work-in-process (WIP) inventory, defect indicators and energy consumption provide complementary measures of operational performance. Although these measures may influence productivity, they are not synonymous with labour productivity. The analysis therefore distinguishes productivity outcomes, process-efficiency measures and resource-use indicators when considering the potential mechanisms of technological impact.

2.2. Research methodology

The research adopts a literature-review approach combined with comparative analysis and thematic synthesis to identify potential applications of AI and smart technologies in garment process innovation. Sources include scientific articles, research reports, technical documentation and reported applications at garment enterprises in Vietnam and internationally. The reviewed studies primarily cover 2015–2026, supplemented by foundational references concerning AI, process innovation and productivity.

Materials were selected on four criteria: (i) direct relevance to technology, production processes or garment manufacturing management; (ii) an identifiable publication source or verifiable provenance; (iii) descriptions of technological functions, implementation conditions or research findings; and (iv) information useful for examining possible implications for productivity, quality or resource efficiency. Materials lacking traceable provenance, adequate substantiation or relevance to the research scope were not used to establish claims of technological effectiveness.

The synthesis groups the evidence into three domains: (i) design, sample development and material preparation; (ii) production-line organization, operations, monitoring and quality control; and (iii) energy management and resource efficiency.

For consistent extraction and comparison, six information fields were specified: production stage, technology type, application function, research evidence, evaluation indicator, and implementation conditions or limitations. These fields organize the evidence and support comparisons between technology applications across garment-production stages, as summarized in Table 1.

Table 1. Information fields used in the literature analysis

Information field	Analytical content
Production stage	Design and sample development; material preparation; line organization and operation; quality control; energy management.
Technology type	AI; digital design; robots and automation; RFID; sensors; production management systems; organizational improvement tools.
Application function	Data collection and connectivity; production monitoring; anomaly detection; prediction; automation; planning and decision support.
Research evidence	Quantitative and qualitative findings; factory application cases; calculations and assessments reported in prior studies.
Evaluation indicators	Labour productivity; line efficiency; manufacturing and changeover time; WIP; defect indicators; energy consumption.
Conditions and limitations	Investment and operating costs; infrastructure; data quality; staff capabilities; equipment integration; study context and evidence reliability.

Source: Developed by the author for literature analysis and synthesis.

The fields in Table 1 make it possible to compare technological functions, reported results and implementation requirements. Importantly, digitization, conventional automation and changes in production organization are distinguished from AI-based analysis, prediction and decision support. Quantitative findings drawn from earlier studies are treated as secondary evidence and interpreted within their original research conditions, rather than as new experimental results of the present study. This synthesis provides the basis for identifying intervention points, necessary data and indicators for the proposed integration framework.

Based on this synthesis, an integrated AI and smart-technology framework is proposed to support process innovation in Vietnamese garment enterprises. It is an implementation-oriented conceptual proposal, not a model empirically validated in the present research.

2.3. Analytical framework

The analytical framework used to synthesize the literature comprises three interrelated layers: (i) production stages; (ii) technologies and data; and (iii) outcomes and evaluation indicators. It organizes prior evidence, identifies potential AI applications and clarifies the relationships between technological functions and operating performance in garment manufacturing.

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The first layer identifies principal production stages: garment design and sample development, material preparation, line organization and operation, quality control, and energy management. It provides the basis for categorizing the reviewed studies by application scope and identifying operational challenges within each stage.

The second layer considers technologies and data available at each stage, including digital design tools, RFID, sensors, robots, automation equipment, production-management systems and AI. Digitization and automation mainly facilitate data collection, connectivity or the execution of production tasks. AI is considered in terms of data analysis, anomaly detection, forecasting and decision support. This distinction is necessary to avoid attributing the results of organizational changes or conventional automation directly to AI.

The third layer examines results reported in previous studies and the corresponding evaluation indicators: labour productivity, line efficiency, production time, style-changeover time, WIP inventory, defect rates and energy use. Conforming output per labour-hour is used as a direct indicator of labour productivity, while the other measures describe different dimensions of operational efficiency and resource utilization.

Cross-referencing these three layers identifies relationships among production stages, data requirements, technological functions and evaluation indicators. This analytical procedure helps identify potential AI intervention points and the practical conditions that would need to be satisfied before implementation in Vietnamese garment enterprises.

The three-layer analytical framework is a method for reviewing and comparing evidence; it is distinct from the four-layer integration model proposed in Section 2.7 below. The latter translates the findings into an implementation concept linking production data, connectivity infrastructure, AI-enabled analysis and operational management. Keeping the two frameworks conceptually distinct clarifies how the literature synthesis informs the proposal and how its effects may eventually be tested.

2.4. Findings and discussion

2.4.1. AI and smart technologies in pre-production

AI and digital technologies can support changes in the garment design and sample-development stages. Huo et al. [3] identify potential AI functions including image analysis, feature recognition, trend prediction and design recommendations. In China, Product AI has been applied to apparel-image recognition and retrieval, while Deep Vogue has used deep-learning methods to assist design development based on image data and user requirements. These examples illustrate potential support for generating and selecting design concepts, but their quantitative effects require validation under clearly specified operating conditions. Beyond AI, three-dimensional design and simulation tools such as CLO 3D enable digital garment prototyping, visualization of shape and structure, and adjustments before making physical samples. At the Portuguese garment company GUIMA, Ha et al. [4] describe the use of design, grading and marker-making tools such as Gerber to support technical preparation and potentially more efficient material use. Design, simulation and marker making, however, must not automatically be described as AI applications. Digital design technologies may reduce technical errors and improve coordination between design and manufacturing, while AI could assist pattern-data analysis, anomaly identification and the suggestion of revisions. Sample-development time, the number of iterations and first-pass sample acceptance are suitable evaluation measures. They primarily indicate pre-production performance; effects on labour productivity must be assessed separately and cannot be established from the current evidence alone.

Smart technologies for material preparation and production planning may improve control over inventory and order progress. The GUIMA case analysed by Ha et al. [4] shows that Tecelagem, FluxoConf and barcode systems can assist capacity-based planning, record work status and update progress data. RFID can identify and track the locations and quantities of materials, while AGVs can transport supplies between warehouses and production areas. These applications support digitization and automation in pre-production, but they are not necessarily AI systems. The additional potential of AI lies in analyzing order volumes, material requirements, inventory, production capacity and schedule progress to forecast needs, identify possible shortages and support material-allocation plans. Material waiting time, shortage frequency and plan-fulfilment rates could serve as indicators. Any incremental benefit attributable to AI would require separate testing and should not be conflated with the contributions of warehouse systems, RFID or automated transport equipment.

2.4.2. Technologies for production-line organization and operation

Automation in cutting and assembly can improve operation speed and accuracy. A Bangladesh study by Mehrin et al. [5] reported a cutting time of 20 minutes per fabric lay with an automatic machine, compared with 60 minutes for a straight-knife cutter; the corresponding equipment efficiencies were 85% and 70%. However, the automatic alternative required three operators instead of two and produced a higher proportion of fabric waste under the study conditions. Thus, faster cutting does not necessarily entail simultaneous improvements in labour productivity and material efficiency. Selection decisions should consider trade-offs among time, staffing, waste and investment cost. Industrial and collaborative robots may support feeding, positioning, holding and transporting fabric components during sewing. Gries and Lutz [6] note that the deformability of textiles and the diversity of garment structures remain technical barriers to automating sewing operations. Robotic systems combined with computer vision may improve material detection and manipulation, but their performance depends on stable feeding processes and product characteristics. AI may use image and operational data to recognize garment components, detect anomalies and support process adjustments. Its incremental contribution must nevertheless be evaluated separately from that of automation equipment, with measures such as processing time, conforming output per labour-hour, defect rates and material waste. Such assessment is necessary before concluding that AI integration improves performance in Vietnamese cutting and assembly operations.

Innovations in line organization and productivity monitoring are particularly important when garment enterprises frequently switch styles. Hossain et al. [7] compared a unit production system (UPS) with a conventional progressive bundle system (PBS) in Bangladesh. UPS performed more favourably on labour productivity and line efficiency in the reported setting. The comparative figures are reproduced in Table 2.

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Table 2. Comparison of operating indicators for UPS and PBS

Indicator	UPS	PBS
Standard minute value (SMV, min)	20.747	21.576
Number of workers	41	42
Labour productivity (garments/worker/10 hours)	16.87	15.79
Line efficiency (%)	57.76	55.39
Defects per hundred units (DHU)	6.91	8.46

Source: Compiled from Hossain et al. [7].

Table 2 indicates that UPS labour productivity was approximately 6.8% higher than that of PBS; line efficiency was 2.37 percentage points higher, and defects per hundred units (DHU) were 1.55 lower. These results indicate an advantage for UPS in the study setting, but investment, maintenance and operating conditions must be considered before adoption elsewhere. They concern a production-organization approach, not a direct AI effect, and should not be generalized to all garment factories. Rapid changeover using Single-Minute Exchange of Die (SMED) and a responsibility-assignment (RACI) matrix can also improve production performance. Mohammad et al. [8] examined three applications in garment factories and reported reductions of 50%–64% in style-changeover time. The findings highlight the importance of standardized operations, clearly assigned responsibilities and coordination in minimizing interruptions and supporting stable production after style changes. Taken together, these results suggest that improvements in production organization and digitized operating data can form a basis for investigating AI in sewing-line management. Data obtained from sensors, intelligent overhead conveyors and records of output, progress, processing times, WIP and equipment status could be used to forecast congestion, identify imbalance and recommend resource reallocations. However, AI's added value should be tested through productivity and process-efficiency indicators under comparable production conditions.

2.5. Smart technologies for energy and resource management

Energy efficiency is another area of process innovation that can reduce costs and improve resource utilization. Khan et al. [9] examined changes to boilers, generators, pumps, motors and lighting at a Bangladesh garment factory. Their calculations indicated potential reductions of 3.75% in energy consumption per unit of output (kWh/kg), 3.65% in natural-gas consumption and 9.78% in greenhouse-gas emissions. These are estimated benefits of equipment-improvement options, not measured post-implementation impacts, and they do not demonstrate a direct AI effect.

In Vietnam, the Ministry of Industry and Trade [12] reported electricity savings of 437,350 kWh at Hue Textile Garment Joint Stock Company through management and equipment-improvement measures. Thanh Cong Textile Garment Investment Trading Joint Stock Company's 2022 annual report [13] describes investments in solar power and other resource-efficiency initiatives. These cases illustrate the relevance of technology and energy management, while the energy profile of integrated textile-and-garment factories should be distinguished from that of sewing operations alone.

With energy-consumption data by machine, sewing line and output, AI might be investigated for demand forecasting, abnormal-consumption detection and operational recommendations. Suitable indicators include kWh per conforming garment and energy cost per unit. These measure resource efficiency rather than directly establishing a rise in labour productivity. The incremental contribution of AI must be tested separately under real operating conditions.

2.6. Proposed integrated framework for AI and smart technologies

Drawing on the reviewed studies of AI, digitization, automation and production-organization improvement [3]–[9], [12], [13], the article proposes an integrated framework designed to support productivity-oriented process innovation in Vietnamese garment manufacturing. The framework's distinguishing feature is its linkage of production data to AI-enabled analysis, managerial action and performance measurement, rather than treating each technology in isolation. It comprises four functional layers and a feedback mechanism through which operational results inform subsequent adjustments (Figure 1).

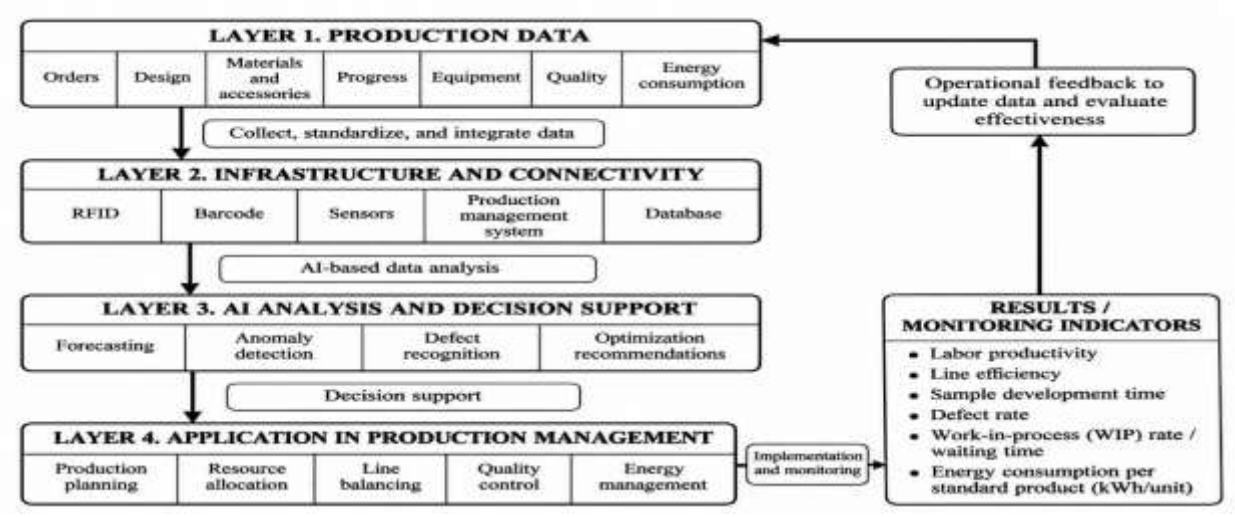


Figure 1. Proposed framework integrating AI and smart technologies in Vietnamese garment production
Source: Proposed by the author based on the synthesis of [3]–[9], [12], [13].

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The framework contains four functional layers. The first comprises input data from orders, designs, materials, schedules, output, quality and energy. The second provides data capture, standardization and connectivity through sensors, barcodes, RFID and manufacturing management systems. The third applies AI to analysis, forecasting, anomaly detection and the assessment of operating options. The fourth translates the analysis into decision support for production planning, material allocation, line balancing, quality control and energy management. Operational outcomes are recorded and fed back into the data system for further evaluation and revision.

In sewing-line management, style identifiers, standard minute values (SMV), process-level output and WIP data may help detect emerging line imbalance. AI is proposed as a means of forecasting bottlenecks and providing information for managers to consider when reallocating work. Its effectiveness would need to be assessed through conforming output per labour-hour, line efficiency and WIP. This is a proposed mechanism, not an empirically implemented or validated system.

Table 3. Proposed AI intervention points and evaluation indicators by production stage

Production stage	Input data	Proposed AI function	Evaluation indicator
Design and sampling	Samples and technical specifications	Anomaly identification; pattern-adjustment support	Sampling time; number of revisions
Material preparation	Orders; standard requirements; inventory	Demand and shortage prediction	Material shortage rate; waiting time
Line organization	SMV; output; WIP; progress	Bottleneck forecasting; line-balancing support	Conforming units/labour-hour; line efficiency
Quality control	Images; defect records	Anomaly detection and classification	DHU; defective product rate
Energy management	Power consumption; run time; output	Energy forecasting and anomaly detection	kWh per conforming unit

Source: Proposed by the author based on the reviewed literature.

The measures in Table 3 provide a basis for stage-specific evaluation. Conforming output per labour-hour directly measures labour productivity, whereas processing time, defects, WIP and energy consumption describe other operational dimensions. To isolate AI's incremental contribution, results should be compared under similar production conditions while considering style mix, workforce skills, equipment and production-organization methods. The proposed framework remains conceptual and cannot establish a numerical productivity gain attributable to AI.

2.7. Implementation feasibility and discussion for Vietnamese garment enterprises

The feasibility of AI and smart-technology adoption in Vietnamese garment enterprises depends jointly on infrastructure, data quality, workforce capabilities and financial resources. The GUIMA case [4] demonstrates the relevance of digitizing and linking information across stages for schedule management and production organization. Transferring these practices to Vietnamese enterprises, however, requires attention to differences in scale, equipment maturity and production systems. Where information on orders, material standards, operation times, output and quality remains fragmented, AI deployment is likely to encounter substantial constraints. Data standardization and interoperability should therefore be established before advanced analysis and AI-enabled decision support.

Evidence from automated cutting [5], UPS/PBS organization [7] and SMED with RACI [8] shows that process-innovation outcomes depend on context and that no solution necessarily improves every performance indicator. Automated cutting can reduce processing time while increasing operator requirements and material loss in the reported comparison [5]. Organizational redesign and standardized changeovers, meanwhile, may improve operations without AI [7], [8]. Consequently, Vietnamese garment manufacturers should select solutions according to actual production needs, data availability and anticipated economic benefits, rather than technological novelty. AI has potential incremental value only if its predictive or decision-support functions address limitations not adequately resolved by existing management systems or automation.

Based on the proposed model, a three-stage AI implementation roadmap is suggested. Stage one digitizes, standardizes and links information on orders, styles, SMV, output, quality and equipment status. Stage two identifies a clearly bounded operational problem supported by available data and measurable indicators for a pilot, such as forecasting material shortages or identifying possible sewing-line bottlenecks. Technical compatibility, the urgency of the problem and operating costs should inform selection. Stage three evaluates outcomes and costs and considers broader adoption only when the pilot demonstrates feasibility. Enterprises at an early stage of digitization should first improve processes and data collection rather than immediately investing in large-scale AI systems.

Evaluation design is critical when assessing AI's contribution to productivity. Production time, line efficiency, defect rates and energy use reflect different aspects of operations but do not individually measure labour productivity. A pilot should therefore prioritize conforming output per labour-hour and supplement it with stage-specific measures. Comparisons should account for style mix, order size, workforce skills, equipment and production organization. Moreover, benefits attributable to digitization, automation or management changes must be separated from AI's additional effects. Because the proposed framework is based on secondary research, the current article does not provide empirical evidence of productivity gains caused by AI; future firm-level studies are needed to address this limitation.

3. CONCLUSION AND RECOMMENDATIONS

3.1. Conclusions

Through comparative literature review and thematic synthesis, the study has organized AI and smart-technology applications across design, material preparation, line operation, quality control and energy management in garment manufacturing. The results indicate that digitization,

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automation and organizational improvements can support more effective operations, but these effects must not be equated with the direct contribution of AI.

The study's main contribution is a four-layer integration framework encompassing production data, infrastructure and connectivity, AI-enabled analysis and decision support, and applications in production management. The framework links input information, analytical functions, management decisions and evaluation metrics and identifies potential AI intervention points at individual production stages. It offers a reference for planning technology adoption in Vietnamese garment enterprises, but has not been empirically validated; no direct AI-induced productivity improvement can be established from this study.

3.2. Recommendations

Vietnamese garment enterprises should prioritize production-data standardization and interoperability, strengthen workforce capabilities and select AI problems that are compatible with their technological, financial and organizational circumstances. Implementation should proceed from data preparation through bounded pilots to evaluation and potential scale-up, supported by cost–benefit analysis.

Future research should validate the integrated framework in Vietnamese factories, using conforming output per labour-hour together with complementary process-performance indicators. Evaluations should account for style mix, workforce skills, equipment and production-organization methods to distinguish AI's incremental contribution and assess potential transferability.

REFERENCES

1) Sài Gòn Giải Phóng, 2026. Vietnam textile industry proposes measures to sustain export growth. Accessed 26 October 2026. https://en.sggp.org.vn/vietnam-textile-industry-proposes-measures-to-sustain-export-growth-post124704.html.
2) International Labour Organization (ILO) and Viet Nam Textile and Apparel Association (VITAS), 2025. Skills for Trade and Economic Diversification: Analysis of the Textile and Garment Industry in Viet Nam. ILO and VITAS, Geneva and Hà Nội. DOI: https://doi.org/10.54394/UVEW3071.
3) Huo M., Tang J., Kim C.S., 2019. Research on Application Prospect of Artificial Intelligence Technology in Clothing Industry. Proceedings of the 4th International Conference on Contemporary Education, Social Sciences and Humanities (ICCESSH 2019), Atlantis Press, pp. 925–928. DOI: https://doi.org/10.2991/iccessh-19.2019.207.
4) Ha L.T., Marques A.D., Ferreira F., 2018. How Industry 4.0 Concepts Are Applied in the Portuguese Clothing Industry: Some Evidences. IOP Conference Series: Materials Science and Engineering, 459, 012044. DOI: https://doi.org/10.1088/1757-899X/459/1/012044.
5) Mehrin S., Hasan M.M., Azad M.L.R., Shahin M.M.R., 2022. Comparative Study on Automatic Fabric Cutting Machine and Straight Knife Cutting Machine. North American Academic Research, 5(5), pp. 103–111. DOI: https://doi.org/10.5281/zenodo.6615342.
6) Gries T., Lutz V., 2018. Application of robotics in garment manufacturing. In: Automation in Garment Manufacturing. Woodhead Publishing, pp. 179–197. DOI: https://doi.org/10.1016/B978-0-08-101211-6.00008-2.
7) Hossain S., Hasan M.M., Bristy B.F., Dey B.S., Saima U.H., Akter M., Elahi S., 2023. A Comparative Study Between Unit Production System and Progressive Bundle System in Apparel Production. Proceedings of the 6th Industrial Engineering and Operations Management Bangladesh Conference, Dhaka, Bangladesh, 26–28 December 2023. IEOM Society International. DOI: https://doi.org/10.46254/BA06.20230076.
8) Mohammad A., Hamja A., Hasle P., 2024. Reduction of changeover time through SMED with RACI integration in garment factories. International Journal of Lean Six Sigma, 15(2), pp. 201–219. DOI: https://doi.org/10.1108/IJLSS-10-2021-0176.
9) Khan S.I., Islam A., Islam M., 2022. Auditing and Energy Efficiency of a Ready-Made Garment Factory in Bangladesh: A Case Study. Energy and Power Engineering, 14(8), pp. 387–403. DOI: https://doi.org/10.4236/epe.2022.148020.
10) OECD, 2024. Explanatory Memorandum on the Updated OECD Definition of an AI System. OECD Artificial Intelligence Papers, No. 8. OECD Publishing, Paris. DOI: https://doi.org/10.1787/623da898-en.
11) OECD/Eurostat, 2018. Oslo Manual 2018: Guidelines for Collecting, Reporting and Using Data on Innovation. 4th edition. OECD Publishing, Paris/Eurostat, Luxembourg. DOI: https://doi.org/10.1787/9789264304604-en.
12) Ministry of Industry and Trade of Vietnam, 2022. Practical benefits of energy conservation in the textile and garment industry. Accessed 26 October 2026. https://moit.gov.vn/tin-tuc/su-dung-nang-luong-tiet-kiem-va-hieu-qua/hieu-qua-thiet-thuc-tu-tiet-kiem-nang-luong-nganh-det-may.html.
13) Thanh Cong Textile Garment Investment Trading Joint Stock Company, 2023. Annual Report 2022. Thanh Cong Textile Garment Investment Trading Joint Stock Company, Vietnam. https://www.thanhcong.com.vn/wp-content/uploads/2023/04/20230419-TCM-Annual-Report-2022.pdf.

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