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A Framework for Selecting AI and Automation Technologies in Production Process Innovation in Vietnamese Garment Enterprises

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ABSTRACT: This study investigates uneven automation in Vietnamese garment manufacturing and develops an evidence-informed framework for selecting artificial intelligence (AI) and automation solutions. It draws on secondary survey evidence concerning equipment automation, inter-stage transport, digital tools, production revenue per employee and defect rates, supported by descriptive statistics, comparative analysis and a focused literature synthesis. Automation scores differ across operations: fabric spreading reaches 3.97/5, whereas final pressing and packaging score 1.81/5 and 2.14/5; transport from sewing to packaging scores only 1.16/5. Net revenue per employee increased from VND 295.7 million in 2020 to VND 367.4 million in 2022, although this nominal financial indicator does not establish technical labour-productivity growth or an AI effect. The paper proposes a four-criterion selection framework—improvement need, implementation readiness, integration cost and expected measurable benefit—and a four-stage, conditional implementation roadmap. The framework is a conceptual decision aid requiring enterprise-level validation; it is not presented as evidence of experimentally demonstrated AI benefits.

KEYWORDS: artificial intelligence, automation; garment manufacturing, production process innovation, technology selection, productivity.

1. INTRODUCTION

Vietnamese garment enterprises operate through interdependent processes, including material preparation, fabric spreading, cutting, sewing, finishing, inspection and packaging. Product diversity, short lead times and labour-intensive operations make coordination between stages as important as individual machine capacity. Digital tools, automation and AI may facilitate process control, defect recognition and production scheduling, but investment benefits depend on the production problem addressed and the existing equipment, data and human resources. Monteiro et al. [1] review Industry 4.0 applications in clothing production, while Guo et al. [2] and Nouinou et al. [3] outline opportunities for AI and data-enabled decision support in apparel and textiles.

A key distinction is that mechanized or programmed automation does not necessarily use AI. Automated cutting and transport systems can execute predefined operations, whereas AI-enabled functions can infer patterns from data, detect anomalies, forecast disruptions or assist decisions. Likewise, improvements attributable to line balancing or standardized work should not be labelled AI effects. Digital transformation research in textile manufacturing highlights the combined importance of technological, organizational and environmental conditions [4]. The practical question for Vietnamese manufacturers is therefore not simply which technology is most advanced, but which solution is appropriate to a specific process constraint and can be evaluated credibly.

This study pursues three objectives: (i) describe the status of automation, inter-stage connections and selected production outcomes; (ii) identify process areas meriting investigation and distinguish conventional automation from potential AI applications; and (iii) formulate a technology-selection framework with explicit conditions for piloting and scale-up. Its contribution is a structured connection between observed production limitations, implementation prerequisites and measurable operational outcomes; it does not claim to have estimated causal effects of AI investment.

2. RESEARCH CONTENT

2.1. Conceptual foundations and research methodology

2.1.1. AI, automation and process innovation

Production process innovation is the introduction of new or substantially improved methods for organizing, operating or controlling production. In garment manufacturing, it concerns not only equipment but also production flow, material movement, quality assurance and coordination. Automation performs actions through specified control logic; AI adds data-based recognition, inference, prediction or recommendations. These technologies can complement one another, but they differ in investment requirements, performance evaluation and governance. The technology–organization–environment (TOE) perspective [5] helps assess fit between the technological solution, firm-level capacity and external conditions. ISO 23247-1:2021 [6], which defines general principles for digital twins in manufacturing, also underlines the relevance of structured data and component connectivity, although adopting this standard is not itself evidence of AI readiness.

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2.1.2. Data sources, measurement and analytical procedures

The paper undertakes secondary-data analysis, descriptive comparisons and thematic synthesis of published research. Three sets of evidence are distinguished: (a) five-point survey scores concerning automation and technological adoption in garment operations (enterprise survey, 2023); (b) aggregate net revenue and employment figures for the Vietnamese apparel-manufacturing industry in 2020–2022, drawn from Vietnamese statistical yearbooks; and (c) illustrative quality-improvement findings reported by earlier studies. The survey scores are reported as published; the available article does not supply individual responses or a sampling file allowing re-estimation of confidence intervals or reliability coefficients. No enterprise-specific before–after AI intervention data were analyzed.

For the financial series, net revenue per employee equals annual industry net revenue divided by the corresponding employee count. Year-on-year percentages are based on unrounded ratios. This is a nominal revenue-intensity indicator, not value added per worker, physical-output productivity or proof of improved production technology. The study compares scores across production stages and reviews candidate interventions in light of technical feasibility, data availability and implementation costs. Previous publications and case-study observations are treated as secondary evidence under their original conditions, not as results generated by the present author.

2.1.3. Analytical framework

The proposed four-stage analytical sequence begins with a diagnosis of operations and outcomes, distinguishes improvement through organization and conventional automation from AI-specific functions, evaluates each option against four decision criteria and proceeds to controlled testing when prerequisites are met. The criteria are used as a structured qualitative checklist rather than a weighted aggregate index: no defensible empirical weights have been estimated. Figure 1 summarizes this sequence.

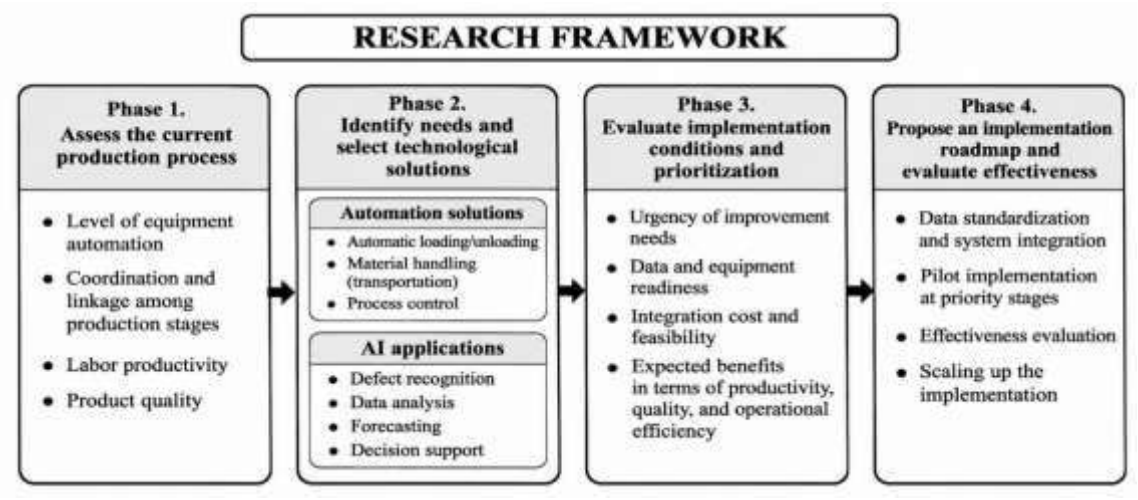

Figure 1. Framework for analyzing and selecting AI and automation solutions in garment production
Source: Proposed by the author.

2.2. Results and discussion

2.2.1. Automation across garment production stages

The 2023 survey scores for 15 production operations reveal non-uniform automation. Fabric spreading attained the highest reported score (3.97/5), followed by cutting (3.38/5) and buttonhole making (3.16/5). Final pressing scored 1.81/5; hem sewing, 2.11/5; and folding/packaging, 2.14/5. This pattern is consistent with uneven opportunities for equipment standardization and the continued importance of manual handling in finishing operations. Nevertheless, a low score is a signal to investigate an operation, not direct evidence that it is the binding productivity constraint. Diagnosis would require cycle-time observations, throughput, waiting times, changeovers and product-mix information.

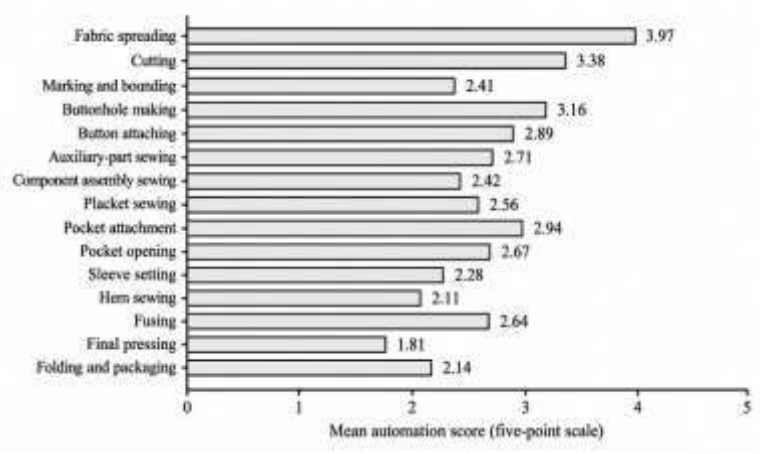

Figure 2. Reported mean automation scores across 15 garment operations (five-point scale)
Source: Enterprise survey, 2023. Selected operation labels are abbreviated in translation.

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Inter-stage movement exposes another mismatch: automated transport within sewing lines scores 3.32/5, but movement from cutting to sewing scores 1.22/5, and from sewing to packaging only 1.16/5. These scores suggest weaker cross-area links than within-line movement. Whether the gap actually causes production delay must be tested using work-in-process levels, movement times, queue lengths and lost production. Table 1 reproduces the inter-stage scores reported in the source study.

Table 1. Automation of linkage and transport between garment production stages

Activity	Mean score /5
Technical design-to-pattern linkage	3.00
Material transfer from warehouse to cutting	1.65
Work-in-process transport from cutting to sewing	1.22
Transport within sewing lines	3.32
Transport from sewing to packaging	1.16

Source: Compiled from the 2023 enterprise survey.

The adoption of management technologies is also differentiated. Computer-aided design (CAD) and 5S/Lean show relatively high usage scores of 4.70/5 and 4.45/5, respectively, whereas speech/image recognition and robots in operations both record 2.22/5. Importantly, 5S and Lean are managerial methods rather than AI technologies, and image-recognition capabilities may be implemented without machine learning. These survey indicators cannot be interpreted as a direct measure of the number of enterprises using AI (Table 2).

Table 2. Use of management tools and digital technologies in garment enterprises

Tool / method	Score /5
Computer-aided design (CAD)	4.70
5S and Lean methods	4.45
Manufacturing execution system (MES)	3.67
Enterprise resource planning (ERP)	3.43
Sensor technologies	3.23
Cloud computing and big data	2.77
Speech and image recognition	2.22
Robots in operations	2.22

Source: Compiled from the 2023 enterprise survey.

2.2.2. Financial-output indicators and garment quality

Across 2020–2022, average net revenue per employee increased from VND 295.7 million to VND 367.4 million. The year-on-year rates were approximately 1.12% in 2021 and 22.86% in 2022, yielding an approximately 24.23% cumulative increase. Revenue, employment and derived ratios appear in Table 3. These values are nominal and can change with selling prices, orders and product mix. The analysis cannot determine whether automation improved technical labour productivity or whether AI was a causal contributor. A credible operational test would require comparable output units, standard labour hours, rejects and cost accounting.

Table 3. Net revenue per employee in Vietnamese apparel manufacturing 2020–2022

Indicator	2020	2021	2022
Net revenue (VND million)	428,772,000	446,026,000	548,897,000
Employees	1,449,929	1,491,557	1,494,086
Net revenue per employee (VND million)	295.7	299.0	367.4
Change from preceding year (%)	—	1.12	22.86

Source: Compiled from Vietnamese Statistical Yearbooks, 2020–2022, as reported in the source manuscript.

Quality data likewise require careful interpretation. A 2019 Vinatex presentation [7] cites a 5–8% defect range for traditional garment processing and a 3–5% reference range for Industry 4.0 approaches internationally; these are not matched enterprise observations and should not be used as an estimated AI effect. In a separate Vietnamese jeans-production case, Pham et al. [8] report a defect-rate decline from 4.40% to 1.06% following DMAIC-based Lean Six Sigma improvement. This result illustrates gains from process management, not AI, and its transferability is constrained by the single-case context.

2.2.3. Potential intervention points and solution differentiation

The diagnostic evidence suggests three broad areas for structured review: weak transport connections between production areas, partially automated finishing operations, and relatively limited adoption of recognition and data-analysis technologies. Initial improvement should examine material-flow redesign, standardized handling, ergonomic work methods and line balancing before considering more complex systems. Grieco et al. [9] provide an example of connected decision-support tools in fashion manufacturing; Chen et al. [10] and Kim and Kim [11] discuss line balancing and work allocation. These references motivate candidate tests rather than prove effectiveness in Vietnamese plants.

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AI may be relevant where a data-rich problem cannot be addressed adequately through fixed rules. Computer-vision defect classification requires representative, accurately labelled images under real lighting and fabric variation; its incremental performance should be compared with manual inspection or simpler vision methods. Predictive maintenance or anomaly detection requires machine-state and downtime records; AI scheduling requires accurate task times and order priorities. A review of fabric defect detection [12] highlights technical possibilities but does not remove the need for local testing. Table 4 aligns each process with potential interventions and verification indicators.

Table 4. Process limitations, candidate technologies and evaluation measures

Process / area	Observed basis	Candidate improvement	Indicators to verify
Cutting-to-sewing and sewing-to-packaging transport	Automation 1.22 and 1.16/5	Redesign material flow; conveyors or WIP tracking; AI dispatch only if data permit	Transport time; waiting time; WIP
Final pressing, hem sewing, folding / packaging	Automation 1.81, 2.11 and 2.14/5	Standard work; dedicated equipment; partial automation	Cycle time; conforming output; labour use
Quality inspection	Quality-improvement need; limited recognition-tool adoption	Computer vision with AI-assisted defect detection / classification	Defect rate; detection precision; misses; inspection time
Production monitoring	MES 3.67/5; sensors 3.23/5	Connect device data; real-time monitoring; AI anomaly alerts	Downtime; plan attainment; alert accuracy
Planning and dispatch	Uneven automation across operations	Integrate production data; optimize or AI-assist scheduling when justified	Schedule deviation; waiting; order lead time

Source: Author's synthesis of the 2023 survey and literature.

2.3. Proposed technology selection and conditional roadmap

Four selection criteria structure the decision: (1) improvement need, expressed as a documented operational problem and baseline; (2) readiness, including data quality, equipment connectivity, workforce skills and governance; (3) cost and integration feasibility, including downtime, training and maintenance; and (4) expected measurable benefits, such as conforming units per labour hour, defect reduction and lead-time improvement. Frank et al. [13] emphasize patterns of Industry 4.0 adoption and the role of complementary technological capabilities. Since empirical weights are unavailable, the four criteria should be assessed separately and discussed transparently rather than collapsed into an arbitrary score.

A conventional-automation alternative must be included in each comparison. For instance, a low-scoring transport process might benefit more from layout changes, standard work or a simple conveyor than from AI dispatch. AI-based defect detection should not be approved solely on laboratory accuracy when false negatives would impose costly downstream rework. The first pilot must define the exact intervention, counterfactual or benchmark, data-collection protocol and acceptance thresholds before implementation. Pilot outcomes should include both technical measures and a full-cost evaluation.

Table 5. Conditional roadmap for AI and automation implementation

Stage	Main activities	Condition for progression
1. Standardize data and processes	Map workflow; collect output, time, defect and equipment-state data; establish baselines	Reliable data and a clearly documented improvement problem
2. Select priorities and options	Apply four criteria; compare organizational, conventional-automation and AI options; define pilot	Technical, data, personnel and cost feasibility; approved evaluation plan
3. Conduct controlled pilot	Test on a bounded process; measure quality, throughput, stability and additional cost	Predefined technical and performance targets met; operational risks controlled
4. Evaluate and scale	Compare results, assess net economic benefits, standardize procedures and decide on extension	Verified net benefit and sustainability; otherwise revise or terminate

Source: Proposed by the author on the basis of the analytical framework and process diagnosis.

2.4. Implications, limitations and further validation

The results reinforce the importance of a system-level perspective. Increasing the capability of an individual machine may yield little plant-wide benefit if upstream material availability or downstream handling remains constrained. The appropriate decision unit is therefore the process flow and its measurable bottleneck, not equipment sophistication alone. The framework also argues for sequencing: first improve process stability and observability; next compare feasible solutions; then test AI only when the additional analytical capability can be justified. Data ownership, operator acceptance, IT security and responsibility for final decisions must be assigned before deployment.

The analysis has limitations. Automation and tool-adoption indicators are from a 2023 enterprise survey, while net-revenue and employment statistics refer to 2020–2022; differences in data scope and time prohibit matched causal interpretation. The survey instrument and unit-level records were not available for independent recalculation. Published quality comparisons arise from distinct production settings. The proposed selection framework and roadmap remain conceptual; neither their decision validity nor their economic benefits have been tested in garment enterprises.

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To make technology choice auditable, the enterprise should prepare a brief decision record for each candidate: the baseline problem, available options, required interfaces, anticipated failure modes, staff responsibilities and the measurement method. These records should distinguish three distinct comparisons: an existing process versus a low-cost management improvement, that improvement versus conventional automation, and conventional automation versus an AI-enabled alternative. Only the final comparison isolates the potential incremental benefit of AI. A decision to proceed should remain reversible where safety, workforce disruption or cost uncertainties are substantial.

Evaluation metrics should be defined at the same process level as the intervention. Conforming units per direct labour hour can capture labour-related operational performance; total output should not be used without checking reject rates and product mix. Waiting time and work-in-process help diagnose material flow, whereas false negatives and false positives are central to inspection systems. For an AI alerting application, an apparently high model accuracy can be misleading when adverse events are rare; precision, recall, missed-defect costs and actionability of alerts may be more informative. Comparisons should use the same definitions, comparable product types and equivalent shifts, with seasonal and order-composition differences documented.

Economic feasibility likewise extends beyond purchase price. The relevant costing boundary includes installation, data annotation, system integration, operator training, production interruption, cybersecurity, model updates, maintenance and eventual replacement. A simple net-benefit assessment can compare verified reductions in rework, waiting or resource consumption with these incremental costs over a specified horizon. Sensitivity checks should cover changes in order volume, product variety and model maintenance effort. Where data quality remains inadequate or the apparent advantage disappears under plausible cost assumptions, postponing the AI investment is a scientifically defensible outcome of the framework.

Further research should apply the framework prospectively at firms of different sizes and production profiles. A transparent protocol could record pre-intervention observations of conforming output per labour hour, WIP, transport times, defects and unit costs; select a matched comparison line or use repeated observations; and document model performance, maintenance and workforce effects after piloting. For AI solutions, classification performance, false-alarm costs, drift and human override should be assessed alongside conventional operational indicators. Such designs would help distinguish process-management gains from any incremental contribution of AI.

3. CONCLUSIONS AND RECOMMENDATIONS

3.1. Conclusions

The evidence shows uneven automation across garment processes and particularly low scores in inter-area WIP transport and selected finishing operations. CAD and management methods are more widely used than recognition and robotic technologies in the source survey, but these indicators do not directly establish AI penetration. Net revenue per employee increased between 2020 and 2022; this nominal trend cannot be equated with technical productivity improvement or attributed to AI. The study proposes a selection framework based on operational need, readiness, integration cost and expected benefits, with a four-stage roadmap that requires evidence before proceeding to broader deployment.

3.2. Recommendations

Garment enterprises should first map and measure the complete process, especially inter-stage transport, finishing and inspection. They should prefer low-complexity organizational improvements where these meet the problem, standardize operating data and assess the incremental value of AI against an appropriate benchmark. Pilots must include pre-specified indicators, maintenance and integration costs, human responsibilities and explicit criteria for continuation or termination. Training institutions, research organizations and technology suppliers should cooperate on data standards, workforce capability and bounded enterprise pilots. Future studies should use contemporaneous, comparable operational data and experimental or quasi-experimental designs to verify the framework and estimate effects without conflating AI with automation.

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