Available on: https://jmrr.ep-journals.org/ E-ISSN: 3051-3588, P-ISSN: 3051-357X

Journal of Management Research and Review

Volume: 02 Issue: 11 November-2026

An Integrated Framework of Quality Management, Lean Manufacturing and Digital Technologies to Support AI Adoption in Vietnamese Garment Enterprises

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Published Date: November 24, 2026 **Article DOI: 10.65150/EP-jmrr/V2E11/2026-12**

ABSTRACT: Productivity in garment manufacturing depends jointly on output quality, production flow, and the reliability of operational information. This paper adopts a qualitative literature review and comparative synthesis of published studies addressing statistical quality control, PDCA, Six Sigma, lean manufacturing, and digitally enabled factory management. The evidence indicates that process improvement techniques may reduce defects and non-value-adding activities, yet reported outcomes vary substantially by production context, metrics, and implementation conditions. Distinguishing digitization, equipment connectivity, and genuine AI applications, we propose a five-layer conceptual framework covering production data, management foundations, digital connectivity, decision support, and performance feedback. A three-stage adoption roadmap is then outlined for Vietnamese garment manufacturers, emphasizing data standardization, selective connectivity, and controlled AI pilots. This paper contributes a structured synthesis and implementation-oriented conceptual framework, rather than experimental proof of AI-induced productivity gains.

KEYWORDS: garment manufacturing, productivity, lean manufacturing, digital transformation, artificial intelligence.

1. INTRODUCTION

Garment manufacturing is labor-intensive, involves successive processing stages and frequent changes in product styles, and operates under short delivery lead times. Sewing-line performance depends not only on direct operations but also on standard times, layout, the quality of fabrics and accessories, defect detection, and the progress of preceding operations. In a study of an Ethiopian garment manufacturer, Mulugeta [1] identified excessive production lead times, poor line balancing, and inefficient movement of work-in-process as sources of waste. Tekletsadik's study of shirt production [2] likewise showed that defects were concentrated in certain categories identifiable through Pareto analysis.

In Vietnam, garment manufacturers must improve labor productivity while meeting quality and delivery requirements, accommodating style changes, and making effective use of existing equipment. Readiness varies across enterprises; replacing all sewing machines with connected equipment is not necessarily appropriate for every facility. Although many studies examine improvement methods separately, an integrated perspective is needed on implementation sequencing and the interplay among quality management tools, Lean, digital production data, and AI, particularly for small and medium-sized enterprises.

This article has three objectives: to systematize experience with quality management innovation, digitally enabled factory management, and Lean; to compare the scope, conditions, and limitations of published outcomes; and to propose an integrated framework and a roadmap for selecting digital and AI technologies suited to Vietnamese garment production. The study is a qualitative comparative literature review proposing a conceptual framework, rather than an experimental evaluation of an implemented AI model.

2. RESEARCH CONTENT

2.1. Theoretical foundations and performance indicators

Productivity in garment enterprises is commonly assessed as acceptable output per unit of input, such as per worker, labor-hour, or sewing-line time. However, higher gross output does not necessarily mean higher effective productivity if defective items, rework, and work-in-process inventories also increase. Productivity assessment should therefore consider quality, cycle time, style changeover time, work-in-process, and equipment utilization. Different indicators can complement one another, but should not be combined into a single improvement rate without consistent definitions and measurement bases.

Quality management involves setting standards, identifying deviations, determining root causes, and verifying improvement actions. Control charts track process variation over time; Pareto charts identify dominant defect categories; and cause-and-effect diagrams depict factors related to people, machinery, materials, methods, and the environment. PDCA establishes an evidence-based learning cycle, while the Six Sigma DMAIC approach provides a more detailed quantitative improvement sequence. The value of these tools lies in data-informed action, not simply in producing more charts.

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Lean focuses on value flow and waste elimination. Two important principles are just-in-time (JIT), which aligns production with actual demand, and Jidoka, which detects abnormalities or defects at the source so that they can be addressed before spreading downstream. Practices such as 5S, sewing-line layout, work standardization, line balancing, rapid changeover, and continuous improvement help stabilize operations. Digital tools can enhance real-time visibility in Lean systems, but Lean remains fundamentally concerned with creating value and eliminating unnecessary work [3].

Digital technologies in production management may be viewed at three levels: digitization of operational records; equipment connectivity and monitoring; and advanced analytical models for forecasting or recognition. Enterprise resource planning (ERP) links order, material, warehouse, production, and financial data. The Internet of Things (IoT), barcodes, and radio-frequency identification (RFID) can provide traceable data when suitably configured. AI may support computer-vision fabric inspection, equipment anomaly detection, or schedule forecasting; however, outcomes depend on image acquisition, defect labels, data representativeness, and accuracy assessment. AI should be treated as a controlled decision-support tool rather than a complete substitute for managers.

2.2. Scope, Sources, and Synthesis Method

This study adopts a qualitative literature review, systematizing Vietnamese and international publications selected by the author and cross-checking publication details against publishers' websites, journals, scientific databases, or DOI records. Sources are divided into three groups: (i) quality control and defect reduction; (ii) digitally enabled factory and supply-chain management; and (iii) Lean, Lean Six Sigma, and the integration of Lean with Industry 4.0. Publications lacking verifiable information, relevance to the argument, or traceable evidence for company-level numerical claims were not used as the basis for quantitative conclusions.

The unit of analysis is a research case or intervention described in each publication. Each source is compared across five dimensions: production context and product type; the management problem; the tool or technology employed; reported metrics and changes; and limitations on transferability to Vietnamese enterprises. Synthesis primarily involves coding intervention categories and comparing mechanisms, supplemented by a table of quantitative findings with qualifications. No weighted average or meta-analysis is undertaken because the studies differ in indicator definitions, sample sizes, observation periods, and the control of confounding factors.

The approach is a purposive qualitative literature review, not a PRISMA-compliant systematic review: a complete search log, screening flow diagram, and risk-of-bias assessment for every publication were not established. Equipment vendors' claims are treated as product information rather than independent experimental evidence. Vietnamese company experiences serve as management illustrations when publicly available data do not permit verification over comparable periods. The synthesized findings provide the basis for proposing an integrated functional framework, a conditional adoption roadmap, and performance measures for subsequent validation.

2.3. Findings and Discussion

2.3.1. Quality Control Process Innovation

Achieving sustainable enterprise development poses substantial challenges for operators and managers, with product quality among the essential conditions for continued operation. Quality control in garment firms covers incoming fabrics and accessories, production preparation and processing, and finished-product inspection. Tekletsadik [2] examined improvements in shirt quality through statistical quality control (SQC), including Pareto and cause-and-effect diagrams. Pareto analysis identified six prominent defects, including sewing faults around shirt cuffs and sleeve edges, detached buttons, puckering at side seams, missing buttons, and visible pocket stitching. Sjarifudin and Kurnia [4] investigated the finishing quality of men's jackets in Indonesia. Their intervention reduced the finishing defect rate from 17.8% to 11.8%, a relative reduction of approximately 33.7%; blistering defects, in particular, decreased from 4.43% to 0.93%.

The use of Six Sigma's DMAIC approach to improve quality in sock knitting was examined by Kurnia and colleagues [5]. In a Bangladeshi garment enterprise, Hanif et al. [6] showed that a traffic-light signaling system could facilitate prompt identification and resolution of sewing-line defects. Their reported mean number of defective items during an eight-hour shift decreased from 4.13 to 1.25. This case highlights the importance of shop-floor communication and feedback even without sophisticated automation. Moin, Hossain, and Baral [7] used total quality management (TQM) tools, Pareto analysis, cause analysis, and team consultation to identify common defects in export-oriented knitwear. Combining quantitative analysis with the knowledge of supervisors and operators helped clarify process-level causes. In Vietnam, Trần Thị Mỹ Dung et al. [8] applied control charts, Pareto diagrams, and cause-and-effect diagrams at Tay Do Garment Joint Stock Company to examine long-sleeved shirt style PEI 44SW9067. Six sewing operations—armhole topstitching, cuff attachment, collar edgestitching, hem turning, side-seam joining, and cuff topstitching—accounted for a cumulative 76.3% of observed faults, close to the 80% pattern commonly associated with Pareto prioritization.

These experiences suggest a quality-improvement sequence: consistently record defects; prioritize critical problems; investigate causes; pilot countermeasures; measure results before and after; standardize work; and maintain control. Digital forms and dashboards are useful only when this sequence leads to action. Before developing computer-vision models for defect recognition, firms need standardized defect taxonomies and labeled image datasets reflecting actual production conditions. Inconsistent definitions across teams or shifts undermine the reliability of automated predictions for operational decisions.

2.3.2. Digital Factory Management Practices

In Turkey, Hugo Boss introduced a participatory information-management approach described as smart data management in 2019 [9]. Technologies such as JUKI's JaNets system and internet-connected sewing machines illustrate the potential for digital monitoring of sewing operations. On-machine terminals or sensors can record operating states and operation counts. However, operators may perform several tasks, rework defective pieces, or provide assistance; thread-trimming counts or motor activity therefore cannot be equated with the number of acceptable finished units. Equipment data need to be linked to style identifiers, operations, good-output quantities, and downtime causes. Supplier-reported benefits should not be treated as independently validated outcomes without suitable evaluation designs. JUKI's DDL-9000C and Brother's S-7300A are examples of digital sewing machines with connectivity capabilities. Their deployment may also require proprietary management software such as JaNets or NEXIO. The original manuscript reports indicative equipment prices of USD 1,000–1,200 per machine, approximately

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1.4–1.6 times those of conventional models; these amounts should be treated as source-specific estimates, not current market quotations. Vietnam's BRAVO ERP system is also described as supporting integrated order-level tracking of materials from initial receipt through completion.

Pal and Yasar [10] examined IoT- and blockchain-supported data management across apparel supply chains, emphasizing distributed information sharing and connected transactions. Changes in consumer purchasing patterns and growing expectations regarding price and service require manufacturers to obtain customer information and analyze production options. IoT-enabled systems and distributed ledgers may help connect material suppliers, intermediaries, manufacturers, distributors, retailers, and customers, improving access to information for operational decisions.

Big data and AI have also been considered for a range of apparel supply-chain activities [11], including the analysis of product information provided by manufacturers and designers, personalized recommendations in apparel e-commerce, and the identification of opportunities for better data management. Computer-assisted techniques may also support the detection of fabric and color defects in incoming textile materials. These potential applications should be differentiated from independently verified productivity outcomes.

In Vietnam, May 10 Corporation has reported using digital management software for materials, finished goods, equipment, inventory reporting, and document management. Its technical departments have used 2D design tools and 3D fitting applications to assess fit, style, and sample parameters and to facilitate remote customer approval. Hue Textile Garment began implementing the GIMM garment-production management system and reportedly replaced it with BRAVO in 2018 for garment operations and financial accounting. These examples illustrate operational digitization, but the manuscript does not present comparable independent outcome measurements for these enterprises.

2.3.3. Lean and Digital Lean Production Management

Lean manufacturing has attracted considerable attention in garment-industry research. It comprises systematic principles and improvement tools focused on customer-defined value and the elimination of waste in the production or delivery process [3]. Two foundational concepts are outlined below.

Just-in-Time (JIT): A pull-based approach that produces only the required type and quantity, at the required time. Production is initiated in response to demand from the next process.

Jidoka: Built-in quality at the source, making abnormalities visible and allowing operations to stop when problems arise, such as missing information or quality defects.

Lean aims to shorten delivery lead times, minimize waste, and increase customer value. In an Ethiopian garment company, Mulugeta [1] examined productivity improvement using Lean tools. Dagne [12] analyzed a customized Lean Six Sigma approach in garment manufacturing. The reported improvements included a 21.77% reduction in non-value-adding transport time, a reduction in material transport distance from 87.5 m to 25 m (71.43%), and an increase in sigma level from 2.71 to 3.28. These findings relate to the particular study context and do not establish a general effect size for all garment enterprises.

Rahman and colleagues [13] examined Lean manufacturing in relation to productivity and sewing-section layout, considering production times, line targets, process mapping, theoretical floor-space requirements, and line efficiency. Belal and colleagues [14] assessed the viability of Lean production practices in the Industry 4.0 era using evidence from B2B garment manufacturing. The manuscript also describes Nam Ha Garment Joint Stock Company as reducing style changeover time from eight to four hours through production-management software, revised line-feeding responsibilities, and layout optimization; this company-specific claim requires direct-source verification before being treated as an independently documented result. Hoàng Xuân Hiệp and Trần Thị Ngát [15] analyzed conditions for Lean deployment amid digital transformation in Vietnam. Taken together with Satoglu et al. [3], these studies support a proposed sequence: standardize and streamline processes first, collect data automatically at value-creating points second, and adopt intelligent analysis only where a clear decision-making problem exists.

In actual sewing-line improvement, the speed of an individual operator is not the sole performance measure. High output at one station can increase work-in-process at the next without raising final line throughput. Lean therefore requires examination of the whole flow, bottleneck identification, and balancing to the production takt. This aligns with observations of workload imbalance, material movements, and waiting time in the Ethiopian case. For manufacturers handling frequent short-run styles, reviewing standard times and redesigning line configurations after each style change should become a routine management activity rather than a one-off design exercise.

Digital technology may either reinforce or undermine continuous improvement, depending on its use. When dashboards reveal station-level results, managers should distinguish defects arising from materials, engineering changes, or machine breakdowns from those attributable to operator actions, rather than assigning responsibility unfairly from a single indicator. Workers and team leaders can help validate indicator definitions, confirm downtime circumstances, and provide feedback on inappropriate alerts. Such collaboration turns operational data into a resource for organizational learning rather than solely an administrative monitoring tool. Productivity measures should also be interpreted alongside finished-goods quality, working time, and occupational safety.

2.4. Synthesis of findings and transferability

Table 1. Selected outcomes of published production management improvement studies

Study	Intervention and context	Reported measure or outcome
Tekletsadik [2]	SQC in shirt manufacturing	67.3% of previously rejected export items accepted after improvement (as reported in [2])
Sjarifudin and Kurnia [3]	PDCA in jacket finishing	Defect rate decreased from 17.8% to 11.8%
Kurnia et al. [9]	DMAIC in sock manufacturing	Defect rate decreased from 11.08% to 5.54%
Hanif et al. [10]	Traffic-light system in ready-made garments	Mean defects per eight-hour shift declined from 4.13 to 1.25

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Mulugeta [1]	Lean at an Ethiopian factory	Productivity increased 16.66%; production lead time decreased 11.8%
Dagne [13]	Lean Six Sigma in garment manufacturing	Labor productivity increased 17.55% in the cited study
Rahman et al. [14]	Lean and sewing-line layout	SMV decreased by 0.9 minutes; output increased by 1,664 units per month

Source: Compiled by the author. Citation labels are reproduced from the original table and require reconciliation against the reference list.

2.5. An integrated quality management–lean–digital technology–AI framework

Based on the reviewed studies, this article proposes an interconnected five-layer framework with feedback. The first layer comprises source data on orders, styles, SMV, acceptable output, defects, downtime, machine states, and materials. The second contains management methods, including Lean, PDCA, SQC, DMAIC, operating standards, and improvement responsibilities. The third is digital infrastructure: electronic forms, selective barcode/RFID systems, ERP, sensors, and dashboards. The fourth provides data-driven decision support, with AI capabilities introduced for appropriate problems. The final layer evaluates outcomes and feeds evidence back into standardization and improvement.

Drawing on the synthesis and comparison of published research, the proposed five-layer model links quality management, Lean manufacturing, digital data infrastructure, and AI-assisted decision support. Figure 1 presents the model's architecture and continuous-improvement feedback mechanism.

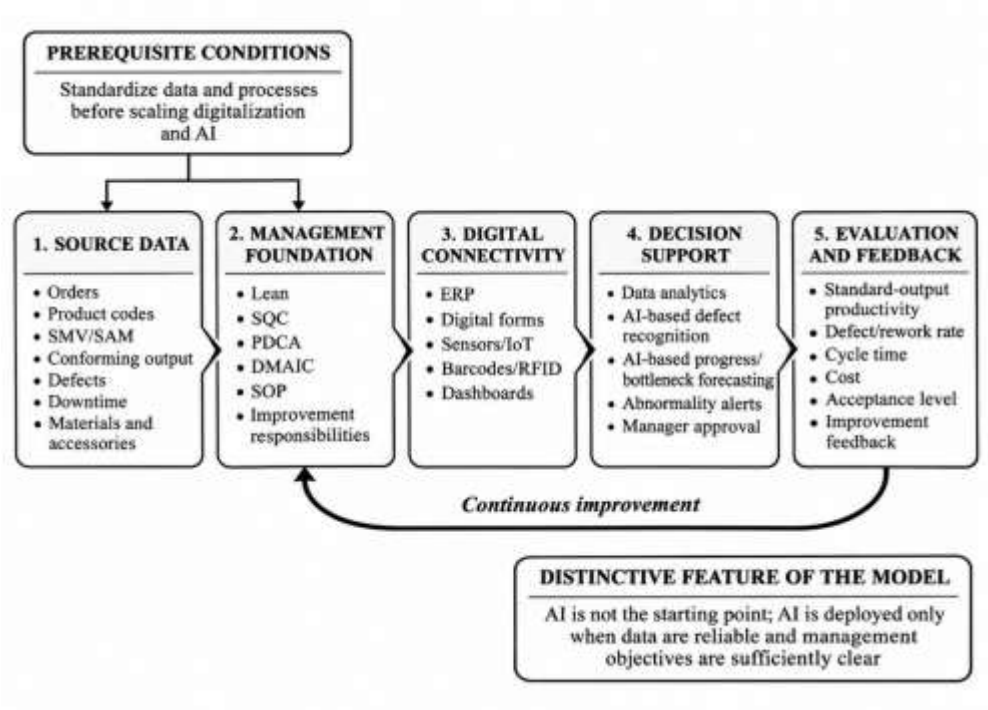

Figure 1. Proposed integrated framework combining lean, quality management, and digital technologies to support AI adoption in Vietnamese garment enterprises

Source: Proposed by the author based on the synthesis and analysis of published studies.

Figure 1 illustrates how the five functional layers reinforce one another. Source data (Layer 1) provide information for production control; management foundations (Layer 2) establish principles, tools, and improvement procedures; digital connectivity (Layer 3) enables data collection and integration across departments; decision support (Layer 4) uses data to detect abnormalities, forecast outcomes, and recommend responses, with AI applied only when data and management objectives justify its use; and evaluation and feedback (Layer 5) measure performance and inform adjustments. Feedback from Layer 5 to Layer 2 creates a continuous-improvement cycle rather than a set of isolated technology projects.

The distinctive feature of this conceptual framework is its sequence from management standardization to data connectivity and AI-supported decisions, rather than starting with technology purchases. Compared with isolated deployments of Lean, quality-management tools, or digital systems, the framework connects input data, improvement mechanisms, connectivity, decision support, and outcome evaluation. AI remains a conditional support function and does not replace managerial oversight. This architecture is intended to accommodate differences among Vietnamese garment firms in size, managerial capability, and digital readiness.

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Table 2. Components and evaluation criteria of the integrated management framework

Functional layer	Content and requirements	Monitoring indicators
Source data	Standard definitions for defects, time, output, and styles	Data completeness; verification discrepancies
Management foundations	Lean, PDCA, SQC, DMAIC; team/shift accountability	Defect rate; rework time; SMV
Digital connectivity	ERP, digital forms, sensors, selective barcodes/RFID	Reporting latency; traceability
Decision support	Anomaly analysis and AI for selected use cases	Forecast error; defect-detection accuracy; processing time
Evaluation and feedback	Before–after comparisons, controls, SOP revisions	Acceptable-output productivity; cost; user acceptance

Source: Proposed by the author.

The framework should not be mistaken for an AI system already in operation. A feasible pilot, for example, could use computer vision to detect fabric defects. Input images would be collected under controlled lighting, labeled according to a taxonomy agreed upon by quality personnel, and evaluated on fabric batches and styles excluded from model training. Performance metrics should include true detections, missed defects, false alarms, inspection time, and operating costs. Human inspectors should retain the authority to review decisions during the initial pilot phase.

2.6. Adoption roadmap, success conditions, and study limitations

Table 3. Proposed Adoption Roadmap for Vietnamese Garment Enterprises

Stage	Key activities	Evidence to collect
1. Standardization	Classify defects; standardize operations; measure times and establish baselines	Defects, SMV, cycle time, acceptable-output productivity
2. Targeted digitization	Connect warehouse and sewing lines; implement digital forms, dashboards, and traceability	Data completeness; reporting delay; alert-response rate
3. AI pilot	Select one use case; establish comparisons; monitor defects and costs	Accuracy; net benefits; stability across style changes

Source: Proposed by the author.

Progression from standardization to digitization and AI adoption should be governed by explicit performance criteria rather than an investment timetable alone. Enterprises need to assess data completeness and consistency, interoperability with existing machines, workforce capabilities, and system maintenance costs. AI should be scaled only when pilot results demonstrate reliability appropriate to production requirements and measurable net benefits after capital, operating, and maintenance costs.

3. CONCLUSION AND RECOMMENDATIONS

The synthesis of studies on SQC, PDCA, Six Sigma, Lean, and digital production management indicates that productivity improvement in garment manufacturing is a systems-management issue. Quality tools can reduce defects and rework costs; Lean can reduce waste and improve flow balance; and ERP, IoT, and RFID can facilitate the capture, integration, and traceability of information. AI may help identify or predict operational problems where suitable datasets exist, but it does not replace process design, work standardization, or accountability. Numerical outcomes reported by individual publications must be interpreted in their specific study contexts rather than as general evidence of AI effectiveness.

The article's contribution is to classify management experiences by function, distinguish three levels of digital technology, and propose an integrated five-layer framework linking source data, management foundations, digital connectivity, decision support, and evaluation/feedback. It provides a prioritization logic: identify a production problem first, establish reliable data and processes before buying technology, and pilot AI only when there are clear measurable objectives. Vietnamese enterprises should prioritize standardized production data and shop-floor quality control, invest selectively in connectivity where benefits are identifiable, choose one AI use case that permits independent evaluation, and scale according to demonstrated results.

Technology providers and enterprise-support organizations should prioritize compatibility with existing machinery, training in digital production management, and transparent performance evaluation criteria. Future research should collect longitudinal data, employ comparison groups, assess costs and benefits, and isolate the contributions of management improvement, digitization, and AI. Until such evidence is available, the proposed framework remains a review-based implementation orientation rather than a model demonstrated to increase productivity in all garment enterprises.

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