RESEARCH ARTICLE OPEN ACCESS

# Artificial Intelligence for Sustainable Textile Manufacturing: Enhancing Efficiency and Sustainability

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## Abstract
Tackling environmental, economic, and social challenges while keeping textile manufacturing competitive requires a transformative shift in the industry's operations. The study presented in this paper looks at the role of Artificial Intelligence (AI) technologies on the journey to sustainable textile production. We examine how machine learning (ML), computer vision (CV), predictive analytics and AI systems that integrate IoT are transforming the way the energy sector uses ML, reduces waste, assures product quality and improves supply chain transparency. Based on our research, the energy savings range between 15-30%, textile waste reduction up to 25% and production yield rates between 10-20% higher with AI based interventions. We also explore the primary challenges for adoption, the cost of implementing and a lack of skills, and outline a gradual integration strategy for manufacturers looking to use AI as a tool for sustainable change. The results of this study support the global paradigm shift to use AI as a key enabler of Industry 4.0 sustainability goals in the textile industry.

**Keywords:** *Artificial Intelligence, Sustainable Manufacturing, Textile Industry, Machine Learning, Energy Efficiency, Industry 4.0, Circular Economy, Predictive Maintenance*

## 1. Introduction
The textile and apparel industry is a worldwide industry that brings in more than USD 1.5 trillion in revenues every year and employs more than 300 million people along its value chain. It is, however, also one of the most water-intensive and polluting industries in the world, accounting for about 10% of global carbon dioxide emissions, 20% of industrial water pollution and a global average of 92 million tonnes of textile waste per year. Consumer perceptions of sustainable products are growing and regulation is becoming more stringent, so manufacturers are now more challenged than ever before to restructure their business models.
To fill this gap, this paper reviews the applications of AI in the context of sustainable textile production in a structured manner. The theoretical framework is provided in Section 2. Section 3 looks at energy and resource optimization applications. Quality control and waste reduction are explored in Section 4. The discussion on supply chain sustainability is explored in Section 5. Barriers to implementation are discussed in the Section 6. A staged introduction is suggested in Section 7 and future research directions are summarized in Section 8.

### 1.1 Research Objectives
This study has four main aims:
To comprehensively map AI applications supporting sustainability goals across the textile industry
- To incorporate empirical studies and quantify reported efficiency and environmental benefits.
- To understand the challenges that AI implementation presents to textile producers and manufacturers

To suggest a science-based model for incremental adoption of AI in keeping with sustainability targets.

  

## 2. Theoretical Framework

This paper employs a lens of analysis that draws from three complementary streams of theory: the Industrial Ecology perspective, which places manufacturing in the context of ecological systems and focuses on resource circularity; the Resource-Based View (RBV) of strategic management which argues that AI capabilities are organizational resources that can produce competitive sustainability benefits; and the Technology Acceptance Model (TAM) which guides analysis of adoption dynamics (Allish S et al., 2024).

### 2.1 AI Technology Taxonomy in Textile Manufacturing

In this study, AI applications in the textile industry are divided into five categories:

| AI Domain | Core Technologies | Primary Application Areas |
|---|---|---|
| Predictive Analytics | ML regression, time-series forecasting | Demand planning, maintenance scheduling, energy forecasting |
| Computer Vision | CNN, object detection, anomaly detection | Defect inspection, pattern recognition, color matching |
| Process Optimization | Reinforcement learning, genetic algorithms | Loom parameter tuning, dyeing process control |
| Natural Language Processing | Transformer models, text classification | Supplier sustainability reporting, regulatory compliance |
| Robotic Process Automation | Collaborative robots, AI-guided arms | Cutting, sewing automation, material handling |

This taxonomy serves as a framework for the following analysis and guarantees a uniform classification of literature findings within the various application fields (Karuppusamy et al., 2025).

## 3. Energy and Resource Optimization

The use of energy is one of the major cost and environmental drivers in the textile industry. The combined electricity and thermal energy requirements of spinning, weaving, dyeing and finishing represent significant demands. There are promising mechanisms for reduction in all of these processes that are supported by AI optimization.

### 3.1 Machine Learning for Energy Forecasting

The use of historical production data, ambient condition data and equipment sensor stream data to train predictive ML models has proven to be a major success for energy management. Yet, Long Short-Term Memory (LSTM) neural networks particularly have been utilized to predict the energy consumption in spinning mills within an hour level, underpinning proactive energy demand-response scheduling that has the ability to diminish the peak loads by 12 - 18 %. Research at plants in Bangladesh and Vietnam shows that aggregate energy savings can reach 15-22% after optimizing motor speed, air compressor scheduling and HVAC systems using the ML (Kuzmichev, 2025).

### 3.2 Water Consumption Reduction in Dyeing

Dyeing of textiles is among the top water intensive industrial processes in the world with 100–150 liters of water consumed per kg of fabric (conventional methods). Using spectrophotometric data in real time and combining it with ML controllers, AI-based process control devices are helping to optimize dye recipes, which cuts down on the amount of water and chemicals used. Reinforcement learning agents trained to optimize dye bath outcomes have successfully reduced water use by 20–30%, without compromising the color fastness performance (Le, 2020).

  

### 3.3 Predictive Maintenance

Energy waste in textile plants occurs not only as a direct result of unplanned equipment failures, but also indirectly due to inefficient start-up cycles. Vibration spectra, temperature profiles and acoustic emissions from looms, spinning frames and finishing equipment are analyzed by AI-based predictive maintenance systems for the ability to detect early failure signatures. In the industrial validation studies, random forest and support vector machine classifiers have successfully been used to improve fault detection accuracy beyond 94%, leading to a reduction of unplanned downtimes by 35-50% when compared with time-based maintenance regimes (Lin & Zhang, 2025).

## 4. Quality Control and Textile Waste Reduction

An important cause of textile material loss and loss of income in the downstream is defective fabric. The manual way of inspection is limited by human fatigue, subjectivity, throughput etc. This is changing with the advent of AI-driven computer vision systems.This is changing with the arrival of AI-powered computer vision systems.

### 4.1 Computer Vision for Defect Detection

CNNs trained on pre-compiled defect libraries can detect defects at line speeds over 400 m per minute, and with 97–99% accuracy, which is much higher than the accuracy of 85–90% that can be achieved by trained human inspectors operating in production. The systems can be installed on a wide range of knit, woven and nonwoven substrates and detect a variety of defects – such as broken ends, holes, oil stains, weaving errors, and color deviations – with sub-millimeter precision (Petrillo et al., 2024).

### 4.2 AI-Optimized Cutting and Pattern Nesting

In apparel manufacturing, fabric cutting will usually result in 10-20% waste. The AI algorithm, based on genetic algorithms and deep learning, maximizes fabric use while using the nesting algorithm to place patterns optimally across the width of the fabric, thereby reducing fabric offcuts. AI extensions on commercial systems like Gerber AccuMark and Lectra Diamino predict savings in fabric of 3-8% per production order, or significant savings in material and cost at volume (Tadesse et al., 2019).

| AI Application | Waste Type Addressed | Reported Reduction | Source |
|---|---|---|---|
| Computer vision defect detection | Downstream fabric waste | 20–25% | Zhang et al., 2023 |
| AI pattern nesting optimization | Cutting room offcuts | 3–8% | Gerber Technologies, 2023 |
| ML dyeing process control | Chemical/water waste | 20–30% | Huntsman Textile, 2023 |
| Predictive maintenance AI | Scrap from equipment failure | 15–20% | Siemens Industrial, 2022 |
| Demand forecasting AI | Overproduction waste | 10–18% | McKinsey & Co., 2023 |

### 4.3 Circular Economy Applications

Artificial intelligence is being put to use on various possibilities of circular economy transition in textile production. Post-consumer recycling feedstock preparation is achievable with automated fiber sorting systems that deliver 95%+ accuracy when sorting polyester, cotton, nylon and blended fibers by near-infrared (NIR) spectroscopy and ML (machine learning) classification methods. Such systems have been commercialised as start-up firms, including Fibersort and Renewlane with the support of EU Horizon research funding (Textile, 2025).

  

## 5. Supply Chain Sustainability and Transparency

From cotton fields to yarn mills, textile manufacturers, and retail outlets around the globe, the textile supply chain is a long and complex process. Every link poses sustainability problems – raw cotton production using pesticides, working conditions in garment factories. Monitoring, verification and sustainability performance improvements across this complex web is possible with the power of AI.

### 5.1 Supplier Risk Assessment

Continuous assessment of environmental and social compliance risks in supply networks using natural language processing models that are trained using supplier audit reports, news streams, satellite imagery and social media data. Brands can use platforms like Sourcemap and Higg Index to leverage the power of the scores generated by ML algorithms and verified certification to prioritize supplier engagement and pinpoint systemic risks before they become a regulatory or reputational issue.

### 5.2 Blockchain and AI Integration for Traceability

AI-powered data validation and blockchain-based immutability are leading to the development of trustworthy supply chain provenance systems for textiles. AI agents are used to verify the input data of the IoT sensors that are placed in the ginning, spinning, and dyeing processes before attaching it to the distributed ledgers, creating auditable records of fiber-to-retail transparency. Examples of pilot deployment by Cotton Connect and Better Cotton Initiative have shown that these systems can improve the transparency of supply chains from about 30% to 85% after two seasons of implementation (Uddin et al., 2025).

## 6. Barriers to AI Adoption in Textile Manufacturing

### 6.1 Financial and Infrastructure Constraints

A major barrier is the upfront cost of the AI systems themselves, which includes the cost of sensors, computing power, software, licenses, and integration services. Payback for turnkey computer vision inspection systems for fabric quality control can range from USD 150,000 to USD 600,000 and the payback period is 2–4 years, depending on the production volume. However, 80% of textile manufacturers worldwide are small and medium enterprises (SMEs) that may not have the capital to make such investments without targeted financial support, nor have the risk tolerance.

### 6.2 Human Capital and Skills Gaps

To effectively implement AI, a range of skills is required, such as data engineering, ML model management, and operational technology integration, which are not prevalent in conventional textile production teams. According to the International Textile Manufacturers Federation (ITMF) survey from 2023, workforce skills gaps were the greatest challenge to AI adoption, with 67% of respondents ranking it as such. Capital constraints and regulatory uncertainty were next at 58% and 41% respectively (Yılmaz et al., 2024).

### 6.3 Data Quality and Governance

High-quality training data is crucial for AI's effective performance, as it must be consistently labeled. Many textile manufacturers do not have a structured data collection system and their production data are collected by paper-based or legacy systems, which are typically siloed. In industrial environments, data cleaning and preparation usually represent 60-70% of the effort and costs involved in the implementation of AI. In addition, there are data sovereignty concerns, especially in the manufacturing community, where companies sharing supply chain data with brand partners may be concerned with governance (Yılmaz et al., 2024).

| Barrier Category | Frequency Cited (%) | Mitigation Strategies |
|---|---|---|
| Workforce skills gap | 67% | Targeted retraining, AI-as-a-Service models, vendor-managed deployments |
| Capital investment costs | 58% | Green financing, leasing models, government incentive schemes |
| Data quality / availability | 52% | IoT sensor deployment, legacy data migration programs |
| Regulatory uncertainty | 41% | Industry standards development, regulatory sandboxes |
| Organizational resistance | 35% | Change management programs, pilot-led scale-up approach |
| Integration complexity | 29% | Modular AI architectures, open API standards |

## 7. Proposed AI Integration Framework for Sustainable Textile Manufacturing

### 7.1 Phase 1: Sense — Data Infrastructure and Instrumentation

The foundational phase is about building solid data collection systems: deployment of IoT sensors in critical equipment, connecting energy and water metering systems, and digitizing process logs. Estimated investment range: USD 20,000-80,000 for medium scale facility. The key sustainability indicators should be identified and baseline measurements be taken for ROI quantification in the next phases.

### 7.2 Phase 2: Think — Analytics & Predictive Modelling

As a result of structured data flows, manufacturers can implement ML-based analytics—namely, energy usage prediction, predictive maintenance models and quality defect classifiers. AWS SageMaker, Google Vertex AI and other niche textile AI companies minimize the need to have internal data science resources (Xu et al., 2025).

### 7.3 Phase 3: Act — Process Automation and Closed-Loop Control

Finally, in Phase 3, AI models move from advisory to autonomous operations: ML controllers adjust the dyeing process parameters while it is running; robotic cutting systems make AI optimized nesting plans; maintenance alerts trigger automatic work orders. Exception handling and model governance will never be without human-in-the-loop oversight. A set of sustainability KPIs should show improvements from a set of baseline metrics in Phase 1.

### 7.4 Phase 4: Review — Continuous Learning and Supply Chain Integration

The mature phase furthers the use of AI upstream and downstream of the manufacturing process with supply chain transparency platforms, AI tools for supplier sustainability assessment and applications of the circular economy such as AI for fiber sorting and recycled content verification. Continuous retraining of models ensures that they perform well as production conditions change over time. At this stage, organizations can anticipate fulfilling the data obligations of the forthcoming directive on Corporate Sustainability Reporting (CSRD) by EU regulation, by providing evidence generated by AI (Yılmaz et al., 2024).

## 8. Discussion

The findings of this review clearly indicate that there are significant measurable sustainability contributions from AI technologies throughout the textile value chain. This is starting to lower the economic hurdles for SME manufacturers to adopt ML, as the cost of sensors continues to fall, cloud access grows, and the development of ML platforms matures.

But there are a few tensions that warrant reflection. But there is a cost associated with the AI systems themselves, including the energy used to train the models, the use of hardware, the life cycle of the hardware, and the emissions of the data centres. These studies suggest that training of large-scale ML models can emit hundreds of kilograms of $CO_2$ equivalent; manufacturers need to focus on deploying pre-trained models and energy-efficient inference hardware.

Second, employment impacts of AI-powered automation in the textile industry in developing countries require policy attention. AI, which enhances human capabilities in quality assurance and process management, can also reduce jobs that are repetitive and are performed in low-wage labor markets. It is crucial to have frameworks in place to ensure just transition pathways are implemented alongside AI deployment programmes.

Third, the paper has the limitation of relying on published case studies and on the performance that is reported by the vendors, which means that less successful implementations are less likely to be reported in published literature. More representative baseline performance metrics should be determined through primary survey research with wider samples of manufacturers.

## 9. Conclusions and Future Research Directions

### 9.1 Future Research Agenda

There are several directions for future research:

Longitudinal empirical research following sustainability KPI trajectories over multi-year AI implementation programs to be able to make more solid causal attributions

Life cycle assessment (LCA) studies that include environmental costs of the AI systems in addition to their operational benefits and calculate net sustainability balances in these studies.

Compare and contrast AI use models (build-own vs. AI-as-a-Service) and their contrasting sustainability performance profiles for SME manufacturers

Research into AI governance mechanisms tailored to textile supply chain data sharing, considering data sovereignty and competitiveness issues

Discussion of gender and labour market equity issues of AI-automated textile industries in the South and South-east Asian production centres (Kins et al., 2024).

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