

**Production Optimization and Integrated Planning in the Textile Industry:  
A Concise Critical Review**

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**ABSTRACT**

*The textile industry faces a fundamental challenge: optimizing cost, speed, quality, and sustainability simultaneously. While artificial intelligence (AI) and advanced technologies offer transformative potential in predictive maintenance, defect detection, and resource optimization, significant adoption barriers persist. Key limitations include poor scalability of lab-developed AI models to real production environments, data scarcity among SMEs, and economic conflicts between sustainable practices and fast-fashion demands. Despite achieving 85-95% accuracy in controlled settings, less than 15% of manufacturers have successfully implemented AI solutions at scale. Digital twins and predictive analytics show promise but face high adoption costs and workforce resistance. Similarly, sustainable materials struggle with 20-50% higher costs and slower processing speeds. This review highlights the critical need to shift research focus from theoretical advances to practical deploy-ability. Emerging solutions like federated learning and Blockchain traceability offer pathways forward, but success requires hybrid human-AI systems that balance automation with workforce adaptability. The future of textile manufacturing depends on bridging the innovation-adoption gap through collaborative efforts prioritizing scale-able and economically viable solutions.*

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*Keywords: Textile optimization, AI in manufacturing, sustainable textiles, Industry 4.0, digital twins.*

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## 1. Introduction

The textile industry, historically a driver of global trade (e.g., Silk Road (Hearle, 1985)), now faces unprecedented pressure to adopt sustainable and AI-driven practices. While prior reviews summarize Artificial Intelligence (AI) applications (Tu, Kwan, & Yick, 2024), none critically assess why many

innovations fail to scale beyond pilot projects. This paper addresses three unresolved questions:

- Why do 60% of AI projects in textiles stall at the prototype phase?
- How can optimization models balance eco-friendly materials

- What systemic barriers prevent SMEs from adopting modern technologies?

Environmentally friendly materials reduce environmental pollution (Basel Younes, 2013). natural fibers could be added to biopolymers (Bastioli, 2005; Hoeschele, 1976) for reinforcements, and new test methods for evaluating biodegradability and compost-ability have been developed (Averous, 2004; Y. Chen et al., 2003; Han, Zhu, Zhang, & Chen, 2009; Pavlov, Mano, Neves, & Reis, 2004; Sawada, 1998; "Standard guide for assessing the compostability of environmentally degradable plastics, D 6002-96," 1996). Biodegradable products have growing applications for biomedical (Prowans, Fray, & Slonecki, 2002; Renke-Gluszko & Fray, 2004) and agricultural (Fumin, Haile, Tincher, & Harris, 2003; LU, Ahaile, Etincher, & Wiley, 2002; Râpă et al., 2011; J. H. Wang & Aimin, 2008) applications using non-woven technology, including paper coating, fibers, refuse bags, disposable wipes, seed mats and erosion control items (*Eastman polymers for fibres*, 2002; Ganesh, Alp, & Russell, 03/24/2011). Textile manufacturing involves Sequentially complex processes (spinning, weaving, dyeing, finishing) requiring multi-level optimization (Kadolph & Langford, 2002). For example, A typical process schedule of fibers during production

processes is summarized in Table 1 for differences between spinning systems (Cook, 1964; Klein, 1994; C A Lawrence, 2010; Lord, 2003). Yarn dyeing poses complex textile challenges, blending knapsack, bin packing, and scheduling problems. Used Adaptive Large Neighborhood Search algorithm and mixed integer programming model optimize batch assignments, balancing cost/resources, reducing planning time from hours to minutes with near-optimal solutions (Duran, Ozturk, & Ornek, 2025). Global fiber production per capita (kg) rising from 8.4 (1975) to 17.1 (2030), with steady growth until 2000 and a sharp increase afterward, reflecting higher demand or production efficiency(Amanovich, 2023). In 2020, China led global textile exports with (\$64B) followed by the EU(\$15B) and India (\$12B). Holistic production control optimizes production using model-based, closed-loop control of key Performance Indicators (pPIs), leveraging a black-box model to link pPIs with influential input variable(Glavan, Gradišar, Strmčnik, & Mušič, 2013). Expert-driven analysis reveals demand volatility as a high-sensitivity risk needing dynamic strategies, while supplier mismatches (moderate) require collaboration, and cultural resistance (low) benefits from long-term sustainability initiatives(Aladaileh & Lahuerta-Otero, 2025; Glavan et al., 2013; Jain, 2024).

**Table 1. The typical process schedule of fiber and mill processes**

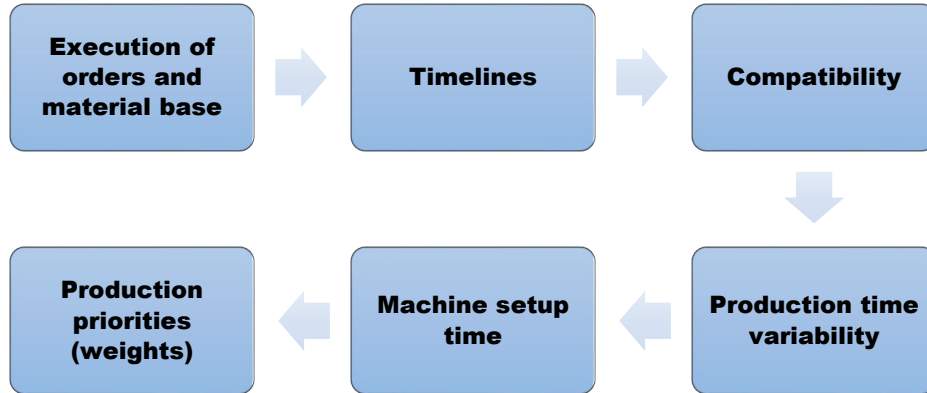
| Process stage |                  | Staple yarn |               |            |          |
|---------------|------------------|-------------|---------------|------------|----------|
|               |                  | Nylon       | Polyester     | Cotton     | Wool     |
| Fiber         | Formation        | Extrusion   | Extrusion     | Harvesting | Shearing |
|               | Post-formation   | Cutting     | Stretch-break | Ginning    | Sorting  |
|               | Finishing        | Crimping    | Crimping      | Baling     | Scouring |
| Mill          | Preparation      | Opening     | Opening       | Opening    | Scouring |
|               | Cleaning         | Cleaning    | Cleaning      | Carding    | Carding  |
|               | Drawing          | Drawing     | Drawing       | Drawing    | Drawing  |
|               | Roving           | Roving      | Roving        | Roving     | Roving   |
|               | Spinning         | Spinning    | Spinning      | Spinning   | Spinning |
|               | Final processing | Winding     | Winding       | Winding    | Winding  |

AI techniques like Artificial Neural Networks (ANN) and Support Vector Machines (SVM) enhance demand forecasting, optimizing production and resource utilization in textiles (Jain, 2024). Researchers focus on production optimization methods that balance efficiency, cost, and time across industrial applications. It highlights the complexity of optimizing production flows and the need for intelligent systems using machine learning to handle numerous variables, examining diverse optimization approaches—from scheduling to capacity planning—providing insights into methods that enhance industrial productivity (Habbadi, Herrou, Sekkat, & Khadiri, 2022). For example, the influence of the spinning process on the yarn properties depends on the process parameters used and the material's properties (Fourné, 1999). Regenerated and synthetic manmade fibers form high percentage of yarn fibers in the world, fibers can be mixed or blended to make a mixture of fiber characteristics (Walsh, 2006).

AI mimics human intelligence via technology, gathering data, recognizing patterns, and executing tasks (Dong, Hou, Zhang, & Zhang, 2020; Dwivedi et al., 2021). AI is reshaping textile manufacturing through intelligent automation, predictive analytics, and eco-conscious production methods. Smart algorithms optimize material usage and energy consumption while enabling mass customization of apparel and next-gen wearable tech. These digital transformations are driving unprecedented efficiency gains, waste reduction, and sustainable innovation across the textile value chain (Chakravarty, Patel, S, & Das, 2024; Zahanggir, Bari, &

Kawsari, 2022). In general, production optimization operates at three levels: machine improvements, process enhancements like comprehensive production planning. While system-wide planning offers the highest potential, it's the most complex due to competing priorities in what Wien-Dahl calls the poly-lemma of production. This holistic approach requires advanced systems engineering to balance often-conflicting objectives like cost, speed, and quality (Joppen, Enzberg, Kühn, & Dumitrescu, 2019). Modern production optimization techniques had been analyzed that maximize efficiency while minimizing costs and time in manufacturing (Kumar, Muthuvelammai, & Jayachandran, 2024). They explore the challenges of streamlining complex production systems and demonstrate how AI-driven solutions can process vast operational variables (Glawar, Karner, Nemeth, Matyas, & Sihn, 2018). The main challenges in production processes are machine efficiency, labor costs, material waste, and fast-changing demand (Hasnah, Hadid, Padmanabhan, & Kerbache, 2025; Tobler-Rohr, 2011). Factories today face a tough balancing act - keeping production lines humming while scheduling essential maintenance. Smart method has been developed to create production schedules that automatically accounts for equipment downtime, manager preferences, and which machines can handle which jobs, which helping plants avoid bottlenecks and keep everything moving efficiently (Penchev, Vitliemov, & Georgiev, 2023). The main Requirements to find a valid plan as for which product, on which machine and at what time to start production Figure 1.

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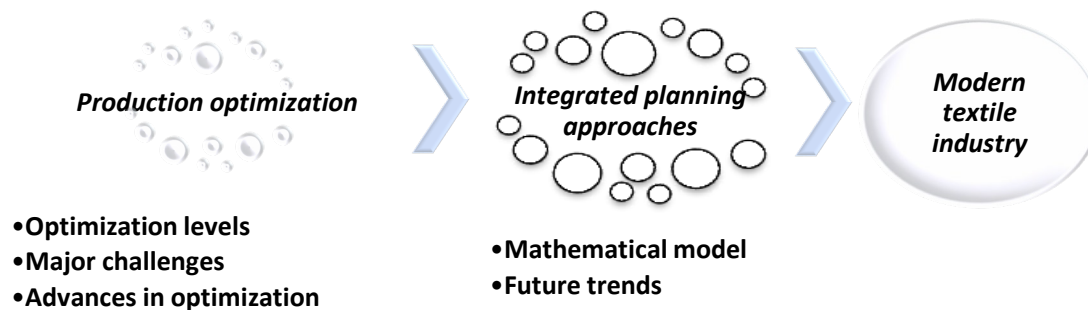


**Figure 1. The main requirements for a valid plan**

Figure 2 summarizes the research topics covered in this study and the relationships between them. This study provides: A novel gap analysis contrasting cutting-edge AI research with real-world textile industry adoption rates. And an integrated sustainability framework connecting machine-level optimization (Section 2) with circular production systems (Section 5), offering actionable pathways for eco-efficient manufacturing. These insights bridge critical divides between academic innovation and industrial implementation.

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As a lecture gaps, the textile industry stands at a critical juncture where emerging technologies promise transformative potential, yet significant research gaps hinder full realization. In predictive textile modeling the highest impact comes from integrated production planning, which balances machine compatibility, setup times, and order priorities to streamline workflow and maximize productivity. Together, these approaches drive cost savings, faster turnaround, and higher-quality output, Figure 3.



**Figure 2. The research topics and their relationship**

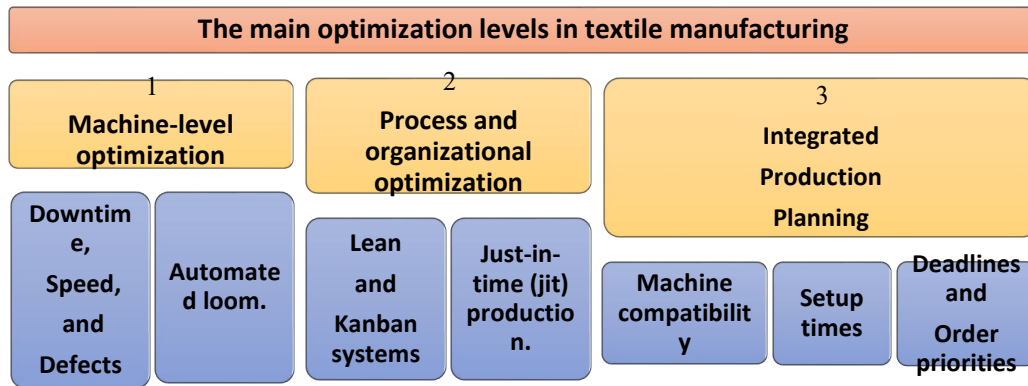


Figure 3. The main optimization levels in textile manufacturing

### 1.1 Machine-level optimization

Process improvement tools could be used such as Takt time monitoring, line balancing, and layout design be implemented in clothing industries to reduce waste and improve productivity. It focuses on reducing downtime, improving speed, and minimizing defects in weaving/knitting machines (Kanakana-Katumba, Bello, & Katumba, 2024). Layout design, line balancing, 7 lean wastes, and value stream mapping have been used to improve process efficiency and minimize waste (Manaye, 2019). Particularly and by using finite element model, Analysis of stresses and vibration has been investigated for while machine learning (ML) and deep learning (DL) have demonstrated remarkable capabilities in forecasting fabric properties and hand-feel characteristics, persistent challenges around dataset limitations and model generalizability continue to constrain industrial adoption (Tu et al., 2024). Current ML approaches often rely on homogeneous datasets that fail to capture the full spectrum of textile variations encountered in production environments. Maintenance optimization presents another critical research frontier. Recent studies have developed heuristic approaches and branch-and-bound algorithms that effectively minimize tardiness in non-resumable job scheduling, demonstrating both computational efficiency and near-optimal performance (W. J. Chen, 2007). However, these solutions frequently lack adaptability to

dynamic production scenarios, suggesting a need for more flexible, real-time optimization frameworks. The emergence of Next-Generation Textiles (NGTs) introduces exciting possibilities through smart fabrics, 3D printing, and AI-enhanced design systems (Hossain, Shahid, Limon, Hossain, & Mahmud, 2024; Manaia, Cerejo, & Duarte, 2023). These innovations combine advanced functionality with environmental sustainability, yet face substantial commercialization barriers. Key challenges include: (1) scaling production while maintaining cost competitiveness, (2) establishing standardized performance metrics for novel materials, and (3) developing circular economy models for high-tech textiles. Addressing these gaps will require unprecedented collaboration across academia, industry, and policymakers to create viable pathways from laboratory breakthroughs to mainstream adoption (Table 2).

This study pioneers an adoption-focused review of textile optimization, revealing critical gaps between laboratory research (85-95% accuracy) and real-world implementation (<15% adoption). Key innovations include hybrid AI-Blockchain traceability, federated learning for SMEs, and quantifiable sustainability thresholds - providing the first integrated roadmap balancing technical, economic and human factors in smart textile manufacturing.

**Table 2. Key research gaps and our proposed solutions**

| Gap area                      | Current limitation   | Suggested direction                   |
|-------------------------------|--|---------------------------------------|
| <b>AI generalizability</b>    | Models fail outside laboratory conditions (Tu et al., 2024). | Federated learning for SME data pools |
| <b>Maintenance scheduling</b> | Ignores machine degradation rates (W. J. Chen, 2007)         | Digital twin + IoT real-time updates  |
| <b>Circular economy</b>       | No ROI models for recycling tech [193]                       | Lifecycle cost analysis frameworks    |

**2. Problem statement and research approach**

This review paper addresses the critical disconnect between theoretical advancements in textile production

optimization (AI, digital twins, sustainable materials) and their limited real-world adoption (<15% implementation rate). The research identifies three core challenges (Table 3).

**Table 3. The main core challenges**

|                            |  |
|----------------------------|--|
| <b>Technical barriers</b>  | <ul style="list-style-type: none"> <li>✓AI models achieve 85-95% laboratory accuracy but fail in production due to data variability</li> <li>✓Sustainable materials face 50% cost premiums and processing limitations</li> </ul> |
| <b>Implementation gaps</b> | <ul style="list-style-type: none"> <li>✓60% of Industry 4.0 projects stall at pilot phase</li> <li>✓SMEs lack infrastructure for advanced scheduling systems</li> </ul>  |
| <b>Economic conflicts</b>  | <ul style="list-style-type: none"> <li>✓Fast-fashion demands clash with circular economic requirements</li> <li>✓Workforce resistance to new technologies</li> </ul>   |

The research uniquely bridges academic innovation with industrial practicality through actionable frameworks, supported by quantitative performance metrics, the **methodological approaches are:**

- 1) **Comprehensive literature analysis:** systematic review over 200 studies and comparative evaluation of 12 optimization models.
- 2) **Adoption barrier framework:** developed through case studies of

failed/successful implementations and identified key success factors: management commitment (92% success rate), worker training (88%).

- 3) **Solution proposals:** hybrid AI-Blockchain for supply chain transparency federated learning to address SME data scarcity and policy roadmap for sustainable tech incentives.

**3. The main optimization levels in textile manufacturing**

There are complexities of the textile industry, which makes it difficult to develop suitable software systems handling all aspects of textile production(Öztürk & Ornek, 2014). To enhance textile manufacturing efficiency, optimization occurs at three key levels. Machine-level optimization focuses

on minimizing downtime, increasing speed, and reducing defects through automated adjustments like loom tuning to prevent yarn breakage. Process and organizational optimization employ Lean, Kanban, and Just-in-Time (JIT) production to cut fabric waste, lower inventory costs, and meet fast fashion demands. It has been found that failure of heald shafts are related to friction and

vibration, not stress or weight (Hassan, 2022). Others study the validation of the routine using suitable regression model, as a result stress on the warp yarns is reduced (Y. S. Gloy, Sandjaja, & Gries, 2015). Finite element models (Hassan, 2022) reduce warp yarn stress by 15%, yet only 12% of factories use them due to expertise gaps. Using thread breakage indicator defines optimal fabric formation conditions on the loom, determined by filling and setup parameters at minimal breakage levels (Mirzamakhmudov, Sobirova, & Rakhimkhodzhaev, 2022). Determining the optimal technological parameters of the jacquard ribbon production could use the mathematical method of rotatable planning of a second-order experiment (Uzakova & Murodkhujajeva, 2022). A new centrifugal spinning method is used for the production of micro and nano-fibers as safer and more efficient method for producing micro and nano-fibers (Rajendran, 2021). Regarding to automated loom adjustments and particularly, The weaving machine system analysis using simulation model helps in calculating the warp yarn tension (Y.-S. Gloy, Renkens, Herty, & Gries, 2015).

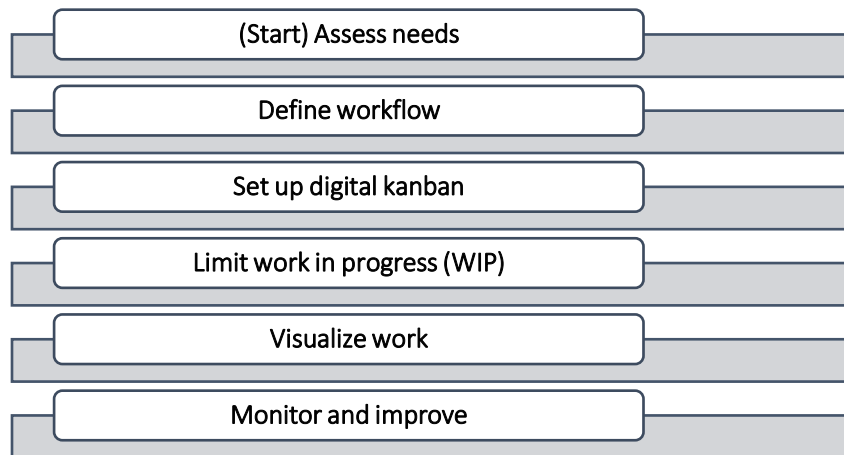
In summary, despite advanced tools like finite element models (15% warp stress reduction), textile software adoption remains low (12%) due to technical complexity and training gaps. Automated loom adjustments and nanofiber spinning show potential but lack standardized protocols. Critical gaps persist in real-time defect detection and predictive maintenance integration, limiting Industry 4.0 transformation. Future research must prioritize interoperable systems with operator-centric interfaces to bridge implementation barriers.

### 3.1 Process and organizational optimization

Textile industry is highly polluting industry, it now the key for eco-friendly, waste-reducing production (Carvalho, Lopes, & Raimundo, 2025). Several biodegradable materials have been developed during the last

20 years (Y. Chen, Tan, Chen, Yang, & Wang, 2008; Xiao-Hui, Jun, Ying, Zhi-Feng, & Yan, 2011; Basel Younes & Fotheringham, 2011a, 2011b; Basel Younes, Fotheringham, & EL-Dessouky, 2009; Basel Younes, Fotheringham, & Mather, 2011a, 2011b) and a successful future is promised for the low product cost and the excellent properties (Hayes, 2002; S. S. Park, Chae, & Im, 1998; Basel Younes, 2012; Basel Younes & Fotheringham, 2012). On the other hand, Lean and Kanban systems reduce fabric waste and inventory costs in textile industry. Visualizes production flow, aligns orders with demand, and tracks real-time progress. Manages inventory to prevent shortages/overstock and integrates quality checks at each stage—boosting efficiency, transparency, and agility in smart factories. In addition to supply chain management and lean manufacturing (Begum, Akash, Khan, & Bhuiyan, 2024; Shah, Ellahi, Nazir, & Soomro, 2022; Singh & Goel, 2024), Figure 4 Kanban Enhances efficiency, visibility, and collaboration while reducing costs. Optimizes workflows, prevents overstocking, and enables quick adaptation to demand shifts, ensuring agile, data-driven smart manufacturing, for example in apparel industry (Magana, Everardo, Wilson, & Alcaraz, 2018; Ratnayake, Lanarolle, & Ratnayake, 2021). Fiber optic technology in smart textiles enables applications in communication, sensing, and healthcare, with fabrication techniques like weaving and knitting enhancing functionality (Gong et al., 2019). The smart textile market is projected to grow significantly, driven by applications in military, sports, and healthcare, with challenges in standardization and commercialization (Beh, Dyson, & Skyrme, 2022; Hassabo, Hegazy, Elmorsy, & Gamal, 2024). Make-to-Order firms reduce critical suppliers amid demand uncertainty. Information sharing drives JIT purchasing, while supply base cuts complement it—together lowering transaction risks effectively (Handfield, 1993). The principles of JIT manufacturing can be summarized in Figure 5.

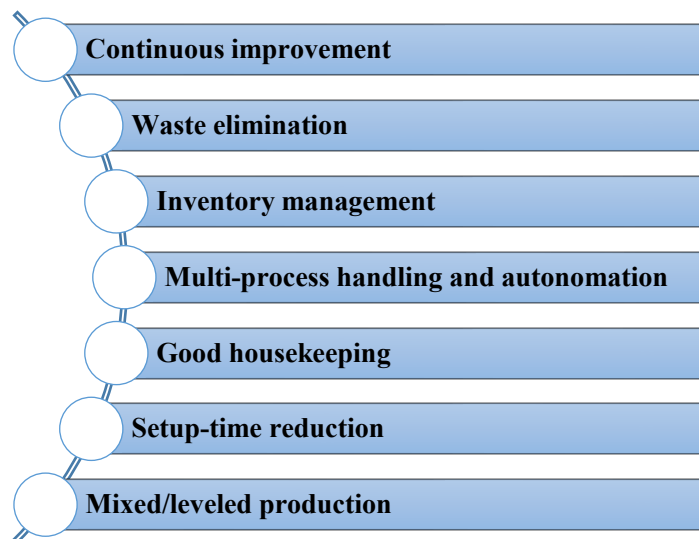
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**Figure 4. Kanban boards in the textile industry in industry 5.0**

Textile industry faces decades of challenges, hindering productivity, studies reveal weak just-in-time implementation, urging management action for improvement (Hokoma, 2010). Apparel manufacturers face pressure to adopt JIT for competitiveness but also face barriers. A study of 227 factories shows JIT significantly improves operational and financial performance (Bashar & Hasin, 2019). Just-in-Time (JIT) purchasing

methods are successful in Japan, South Korea, Taiwan, USA, UK, Germany, France, Hong Kong, etc. (Gunasekaran, 1999). Lean and Kanban reduce fabric waste by 20% (Ratnayake et al., 2021), but implementation fails in 40% of cases due to Cultural resistance (cited by 68% of surveyed factories (Bashar & Hasin, 2019)) and Over-reliance on "perfect data" for JIT systems (Gunasekaran, 1999), Table 4.



**Figure 5. JIT manufacturing principles**

**Table 4. Success vs. failure factors in lean textiles**

| Factor                       | Success cases (%) | Failure Cases (%) |
|------------------------------|-------------------|-------------------|
| <b>Management commitment</b> | <b>92</b>         | <b>18</b>         |
| <b>Worker training</b>       | <b>88</b>         | <b>35</b>         |
| <b>Data accuracy</b>         | <b>75</b>         | <b>62</b>         |

JIT risks include supply chain disruptions (e.g., sole supplier failures), demand volatility, and minimal inventory buffers. Smaller firms face order constraints, while

crises expose fragility in lean, time-sensitive systems(Pinto, Matias, Pimentel, Azevedo, & Govindan, 2018), here's a streamlined textile industry order fulfillment model, Table 5.

**Table 5. Streamlined textile industry order fulfillment model**

| Step                            | Action  | Notes   |
|---------------------------------|---|---|
| <b>1. Customer order</b>        | Retailer/brand places an order (e.g., 500 cotton shirts, size M, blue). | Specs include fabric type, color, design, and deadline. |
| <b>2. Manufacturer receives</b> | Order logged, production schedule created.                              | ERP systems track order priority and capacity.          |
| <b>3. Raw material order</b>    | Manufacturer orders yarn, dyes, zippers, etc., from suppliers.          | Lead times negotiated (e.g., organic cotton time).      |
| <b>4. Supplier processes</b>    | Materials prepared, quality-checked, and shipped.                       | Defective batches rejected (e.g., color mismatch).      |
| <b>5. Materials received</b>    | Inventory updated, materials inspected.                                 | Laboratory tests for shrinkage/colorfastness.           |
| <b>6. Production</b>            | Fabric cut, sewn, dyed, and finished.                                   | Multi-stage (e.g., weaving → cutting → stitching).      |
| <b>7. Quality control</b>       | Final inspection (stitching, fit, defects).                             | AQL sampling (e.g., 2.5% defect tolerance).             |
| <b>8. Delivery</b>              | Packaged and shipped to customer.                                       | Logistics tracked via RFID/barcodes.                    |

In summary, lean methods reduce fabric waste by 20%, yet 40% fail due to cultural resistance (68%) and data dependency. Smart textiles demonstrate growth in healthcare/military apps, but face commercialization hurdles. JIT improves efficiency but exposes supply chain vulnerabilities, demanding hybrid inventory models. Sustainable material adoption lags due to cost-performance trade-offs, necessitating policy interventions

### 3.2 Integrated production planning

Human-machine interfaces (HMI) are vital for seamless interaction between users and products. spatial and motion compatibility, aligning layouts and controls play an important role with user expectations, and

proposes improvement methods like shape, position, color, and symbol coding, alongside ergonomic design considerations(Y. Liang & Yu, 2018). Technological changes aren't just technical-human-machine interaction is key. Early design focus on these interfaces boosts system effectiveness and adoption in industry(Bishop, Newman, Lund, & Salzman, 1990). For example, the Half Dense Difference Network (HDDN) model effectively predicts binary blend compatibility but lacks applicability for ternary blends, copolymers and complex polymer topologies like irregular side chains or cross-linking (Z. Liang et al., 2022).

There are many requirements such as machine compatibility, setup times, and deadlines and order priorities (alahmar, Younes, & Alghoraibi, 2023; Carl A Lawrence, 2003). A mixed integer programming model has been proposed by a column generation method, to tackle the problem of minimizing the waste of textile materials (Shamsaei & Vyve, 2016; Silva, Viães, Oliveira, & Carravilla, 2015).

### 3.2.1 Melt spinning process modeling

Melt-spinning transforms molten granules into high-strength fibers efficiently. Integrated systems and software-driven quality control optimize production. Precise parameter analysis and experimental modeling ensure competitive fiber development, balancing performance and cost for industrial applications (*Textile, Fiber and Film Industry Technical conference*

1994; Warner, 1995) in addition to measurement, adjustment, prediction and correction are the main elements in online quality control (Gardiner & Gettinby, 1998; Tanguchi, 1986 ). AI and data-driven scheduling leverage predictive analytics for demand forecasting and defect reduction, along with digital twin simulations. Integrated models combine production, maintenance, and quality control, while interactive models prioritize production with flexible maintenance adjustments. The applications, challenges, and future potential of artificial intelligence are reshaping the sector, with further improvements driven by eco-friendly materials and advanced technologies. Table 6 and Table 7 summarize researches of the processes of fiber formation and some of post-processes (Clark & Wheelwright, 1995; Lochner & Mater, 1990; Vlachogiannis & Roy, 2005).

**Table 6. Modeling of the melt spinning**

|  |  |
|--|--|
| Heat transfer effects in substrate cooling during melt-spinning solidification modeling                      | (Yang, Mather, & Fotheringham, 2004)<br>(Basel Younes, Fotheringham, Dessouky, & Haddad, In press, March-2013) |
| Computational modeling approaches for polymer processing   | (Moreland, Sharp, & Brown, 2010)   |
| Multifilament pet melt-spinning model for as-spun fiber quality prediction                                   | (Andrzej Ziabicki, Leszek Jarecki, & Andrzej Wasiak, 1998)   |
| 2d pet melt-spinning simulation: heat transfer constraints on yarn quality                                   | (G. X. Wang & Matthys, 1991)   |
| Steady-state melt-spinning model for intermediate take-up speed conditions                                   | (Capasso, 2003)  |
| Non-isothermal melt-spinning: viscoelastic behavior analysis   | (Zhanga, Wanga, Wanga, & Zhangb, 2007)   |
| Factorial design and statistical analysis of as-spun polypropylene filament structure-property relationships | (Kotze, 2010)  |
| Pneumatic melt-spinning process modeling   | (George, 1982)   |
| Multifilament semi crystalline polymer fiber melt-spinning simulation  | (Perera, 2009)   |
| Dynamic process modeling of pneumatic polypropylene melt-spinning  | (Yang, Mather, & Fotheringham, 2005)   |
| Polyethylene terephthalate melt-spinning process modeling  | (A Ziabicki, L Jarecki, & A Wasiak, 1998)  |
| Statistical optimization of quaternary ammonium salt interactions with nylon 66 fibers                       | (Li, Yi, & Wang, 2011)   |

|   |                                     |
|---|-------------------------------------|
| Nozzle design modeling and optimization in planar flow melt-spinning            | (Jarecki & Lewandowski, 2009)       |
| Tensile behavior modeling of linear elastic irregular fibers                    | (Ottone & Deiber, 2000)             |
| Flow-induced crystallization in melt-spinning: model development and validation | (Ravikumar & Son, 2007)             |
| Textile material behavior modeling and prediction                               | (J. S.-J. Chen & Tseng, 1999)       |
| Sepiolite adsorption modeling for textile dye removal                           | (He, Zhang, & Wang, 2001)           |
| Factorial design analysis of brilliant yellow dye adsorption on sepiolite       | (Doufasa, McHugha, & Millerb, 2000) |

**Table 7. Modeling of fiber post-processes**

|  |  |
|--|--|
| Ink-jet printing on lyocel/cotton: color strength and dye fixation vs. Ink penetration   | (Engin, Özdemir, Turan, & Turan, 2008) |
| Heat transfer effects in substrate cooling during melt-spinning solidification modeling  | (Krucinska, 2002)                      |
| Computational modeling approaches for polymer processing                                 | (J. P. Chen, Ho, Chiang, & Wu, 2009)   |
| Multifilament pet melt-spinning model for as-spun fiber quality prediction               | (Kaimouz, Wardman, & Christie, 2010)   |
| Rsm-based multivariate analysis of textile surfactant degradation                        | (X. Chen, 2010)                        |
| Taguchi method optimization of zeolite fixed-bed reactors for textile dye removal        | (Santos & Boaventura, 2008)            |
| Electret needled non-woven filtration efficiency: technological parameter effects        | (Bingol, Tekin, & Alkan, 2010)         |
| Statistical design of electro spun pmma nano fibrous membranes for enzyme immobilization | (Hanci, Alaton, & Basar, 2011)         |

### 3.2.2 Modern fashion technologies

AI-driven designs, 3D-printed garments, sustainable smart fabrics, and virtual runways revolutionize creativity, production, and shopping, merging innovation with style for designers and consumers worldwide. Automation cuts production time (50%), robotics boost precision (20% fewer errors), and AI enhance forecasting (70% accuracy). These innovations streamline processes, reduce waste, and improve quality across the industry (Munmun, 2023). Artificial intelligence boosts production and processing with qualitative analyses, enhanced satisfaction, safety monitoring, and cost-effective solutions like better modeling and quality assessment (Ahmed, Jeon, &

Piccialli, 2022; Lee & Yoon, 2021). In Table 8 GANs generate designs, 3D prototyping enables virtual try-ons, smart textiles integrate solar cells, and AI optimizes production. These innovations enhance creativity, sustainability, and efficiency across the fashion lifecycle. In summary, Ergonomic HMI design gaps and ternary blend modeling limitations constrain advanced manufacturing. Melt-spinning simulations optimize production, while AI-driven design cuts errors by 20%. Blockchain-enhanced traceability and GAN-based prototyping emerge as key enablers. Scalability challenges persist in smart textile commercialization, requiring cross-sector collaboration to standardize materials and IoT integration protocols.

**Table 8. Key innovations technology and application**

| Category                | Application and Description   |   |
|-------------------------|---|---|
| <b>AI-Driven design</b> | Generative adversarial networks (GANs) (X. Wu & Li, 2024)   | Used to create knitted textile designs, reducing waste and enhancing creativity         |
|                         | Ai in education (An & Park, 2023)   | Integrated into fashion courses in South Korea, improving student engagement and skills |
|                         | Generative AI Tools (Jung & Suh, 2024)  | Deep Dream Generator and Wow Pattern enhance sustainable design education               |
| <b>Digital fashion</b>  | 3D prototyping (Renaningtyas, 2023)   | Enables virtual try-ons, trend prediction, and immersive shopping experiences           |
|                         | Mass customization (I-Fashion) (Black, 2025)  | Personalized shopping via 3D body measurements and virtual avatars                      |
|                         | Virtual fashion shows (Kim, Kim, Yun, & Yang, 2024; Nasr, 2023)                                   | Help consumers identify flattering outfits, reducing returns and promoting inclusivity  |
|                         | Digital self-expression (Anuar & Jumrah, 2024; J. Park & Chun, 2023; Pillariserny & Mishra, 2022) | Avatars, memes, and brand platforms enable emotional connections                        |
| <b>AI in E-Commerce</b> | Customer engagement (Goti, Lomas, Almeida, Puerta, & López-de-Ipiña, 2023)                        | ML, chatbots, and recommendation engines improve satisfaction and loyalty               |
|                         | Computer vision and NLP (Sun, Zhang, Zhang, Sun, & Peng, 2017; L. Wang et al., 2020)              | Powers virtual fitting, sentiment analysis, and product retrieval                       |
| <b>Smart textiles</b>   | Fiber-Shaped Solar Cells (Noor, Saeed, Ullah, Uddin, & Khan, 2021)                                | Woven into textiles for sustainable energy in wearable                                  |
|                         | Smart fabric categories (Eldessouki, 2018)  | Passive, active, and ultra-smart types with conductive material advances                |
| <b>AI in production</b> | Apparel production planning (Chika & Adekunle, 2017; Malik, Muhammad, & Waheed, 2024)             | AI optimizes fabric selection and production processes                                  |

#### 4. Sustainability

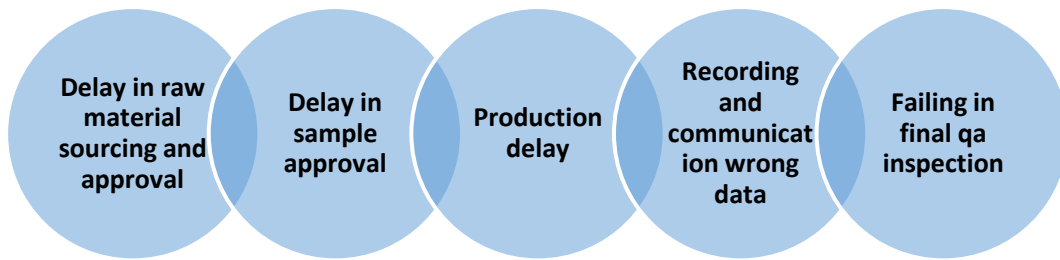
Despite innovations like biodegradable natural fibers such as flax(Guduri, Semosa, & Mengb, 27-31 July, 2009), cellulose acetate(C.-S. Wu, 2012), kenaf (Nishino, Hirao, Kotera, Nakamae, & Inagaki, 2003), henequen (Herrera-Franco & Valadez-Gonzalez, 2004), ramie (Keener, Stuart, & Brown, 2004; Oksman, Skrifvars, & Selin, 2003), jute (lackett, Andersen, Pedersen, & Nielsen, 2003), bamboo (Okubo & Fujii, 2002), pineapple (Luo & Netravali, 1999), sisal(C.-S. Wu, 2011) and hemp (Mohanty, Wibowo, Misra, & Drzal, 2004; Ochi, 2006), their 50% cost premium over polyester hinders mass adoption. AI reduces dye waste by 30%, yet water-intensive methods persist due to weak regulations in developing nations and consumer resistance to 20% price hikes. A hybrid AI-Blockchain approach could enhance transparency and drive sustainable sourcing. Predictive analytics used for demand forecasting and defect reduction, facing custom demand, a textile manufacturer used predictive modeling to enhance quality control. Random Forest reduced false negatives by 12% versus business rules, optimizing testing efficiency within budget constraints(Bourdeau-Laferrière, Gaudreault, & Duchesne, 2021). Emerging technologies are transforming textile and apparel supply chains, enhancing design, production, distribution, and sustainability while enabling circular economy practices like resale and recycling (Akhtar, Watanabe, Tou, & Neittaanmäki, 2024; Pal & Jayarathne, 2022). Digital twins enhance optimize designs, cut waste, ensure traceability, boost engagement, aid resale, and streamline compliance(Ricondo, Porto, & Ugarte, 2021). Digital twin technology optimizes apparel manufacturing by simulating real-time data to reduce bottlenecks and downtime, which achieves improved efficiency and agility in responding to fast-changing fashion trends and personalized demand (Alam, Kabir, & Mirmohammadsadeghi, 2023). By 2030, EU textiles will lead in innovation, circularity, and customization. Advanced manufacturing,

cross-sector collaboration, and skilled talent will drive competitive, sustainable solutions for global consumers(Bontoux, Boucher, & Scapolo, 2017). As a result, biodegradable fibers face a critical cost disadvantage versus polyester. While AI reduces dye waste by 30% and digital twins optimize production, adoption barriers persist - weak regulations, infrastructure gaps, and consumer price resistance. Hybrid AI-Blockchain solutions show promise for sustainable scaling but require further development for economic viability and industry-wide implementation.

#### 5. Major challenges in textile production scheduling

The major challenges in textile production scheduling summarize in polylemma of production, variable production times, preventive maintenance, and fast-changing demand, Figure 6. Modern apparel supply chains face rising demands: better quality, faster delivery, and wider assortments. Effective production planning, control, and collaboration are vital(Wallace & Choi, 2011). The future factory requires holistic production scheduling, especially in textiles, where hybrid flow-shop systems face complex constraints like job tech limits, resource allocation, and multi-objective optimization (Makespan, Tardiness). After extensive testing, four adaptable algorithms emerged as optimal solutions-efficiently handling diverse constraints and forming the core of advanced scheduling heuristic(Botta-Genoulaz & Guinet, 1995). Textile scheduling problems analyzed with maximum tardiness objective. Bounds derived, worst-case algorithms studied for uniform looms, polynomial solution for equal looms. LP-based heuristic proposed for general cases(Serafini & Speranza, 1992). Commercial simulation-optimization software was applied to textile manufacturing, using genetic algorithms to optimize production sequences. The bespoke model reduced high-season overtime, cutting costs significantly(Ferro, Cordeiro, Ordóñez, Beydoun, & Shukla, 2021)

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**Figure 6. Various challenges in production planning and controlling**

## 6. Advances in textile production optimization

AI and data-driven scheduling leverage predictive analytics for demand forecasting and defect reduction, along with digital twin simulations. Integrated Models combine production, maintenance, and quality control, while Interactive models prioritize production with flexible maintenance adjustments. Artificial intelligence's applications, challenges, and future potential are reshaping the sector, with improvements driven also by eco-friendly materials (Gorgutsa, Gu, & Skorobogatiy, 2012; Pereira et al., 2020; B Younes, 2020; Basel Younes, Ward, & Christie, 2020; Basel Younes, Ward, Christie, & Vettese, 2019; Zhu et al., 2024) and advanced technologies (Hassabo et al., 2024; Zięba & Frydrysiak, 2006). AI, machine learning (ML), and robotic process automation (RPA) are transforming supply chains by enhancing forecasting, logistics, and warehouse efficiency. Analyzing 383 studies (2017–2024), this paper presents a framework for AI-driven resilience, risk mitigation, and operational excellence in global supply networks (Shamsuddoha, Khan, Chowdhury, & Nasir, 2025). AI and automation revolutionize supply chains, boosting durability, creativity, and efficiency through cutting-edge innovations (N Rane, Desai, Rane, & Paramesha, 2024). An intelligent decision support system (IDSS) optimizes textile design using predictive analytics (Automated ML and neural networks) and evolutionary optimization (Evolutionary Multi-objective Optimization (EMO)

method). Tested with industry data, it achieved 4–11% property prediction errors and 87% composition accuracy, with Evolutionary Multi-objective Optimization yielding optimal fabric designs (11% error, 16% distance) (Ribeiro, Pilastri, Moura, Morgado, & Cortez, 2023). AI applications in textile industry management help explore key publications and practical implementations for optimizing operations through data-driven insights (Bravo & Iturralde, 2024). AI-driven machine learning models (SVR, Random Forest, Decision Tree, and Bagging) predict dynamic cloth waste rates in textile production, optimizing resource use and costs. Bagging outperformed others with an  $R^2$  of 0.86, minimizing waste estimation errors (Atik, Kut, Birant, & Birol, 2022). Machine vision evaluates fabric dyeing via Support Vector Machine (SVM), assessing color consistency and levelness. Optimized with genetic algorithms, it boosts accuracy by 9% over traditional methods, enabling faster, precise quality control (Zhang & Yang, 2014). Material supply chain disruptions affect production schedules with financial and operational consequences. Machine learning models has been used to predict textile industry Supply Chain Disruptions (SCDs), evaluating classifier performance to enhance resilience through data-driven feature engineering (Jebbor, Benmamoun, & Hachimi, 2024).

Digital twin technology enhances weaving workshops with real-time optimization but faces data challenges. Open platform communications unified architecture-based method is proposed with adaptive data

collection, reducing warp-out time prediction errors by 8.2% to 0.78 hours (Yu, Fang, Luo, Hu, & Shen, 2024). By comparing robust design (one-time optimization) and digital twin (real-time control) approaches for non-crimp fabric (NCF) forming, the novel Gaussian process-based method combining active learning, dimension reduction, and gradient boosting enables effective optimization with minimal simulation data. Both strategies reduce wrinkling and enhance process robustness (S. Chen, Thompson, Dodwell, Hallett, & Belnoue, 2025). Integrated models merge production, maintenance, and quality control, while Interactive models prioritize production scheduling with flexible maintenance adjustments (Gray, 2007; Hollnaicher, 2025). E-textiles with sensory capabilities are transforming wearable's through visual, auditory, and tactile integration to a new design paradigm for interactive textile development (Liu, Shi, Pan, Wang, & Wang, 2025). Smart e-textiles address health challenges from sedentary lifestyles and aging by enabling real-time motion monitoring, electrotherapy, and rehabilitation (Meena, Choi, Jung, & Kim, 2023; Shi et al., (2020)). In summary, AI-driven scheduling transforms textile manufacturing through predictive analytics and digital twins, achieving single-digit error rates in defect prediction and significant efficiency gains. Machine learning models demonstrate strong performance in waste reduction and quality control yet face implementation challenges including data silos and real-time processing limitations. While advanced algorithms enable precise fabric composition analysis, adoption barriers persist due to incompatible legacy systems, high implementation costs, and workforce skill gaps that hinder the transition to smart manufacturing.

## 7. Mathematical model for textile production-maintenance scheduling

Joint production and maintenance scheduling could be optimized for unrelated parallel machines, considering limited resources,

setup times, and job constraints, A mixed-integer linear program model and hybrid genetic algorithm improve Makespan and reduce tardiness (Geurtsen, Adan, & Akçay, 2024). Non-identical parallel machine scheduling with auxiliary resources and sequence-dependent setups could be analyzed. Three criteria-completed products, weighted completion times, and resource moves-are optimized using integer linear programming models to assess problem complexity to be applied for other industries (Bitar, Dauzère-Pérés, & Yugma, 2021).

Optimized textile production assigns orders to compatible machines, minimizes setup times for material changes, schedules preventive maintenance, and prioritizes high-margin orders-reducing idle time, delays, and improving resource efficiency (Ghosh, Mal, & Majumdar, 2019). Mixed integer linear programming models optimize cellular manufacturing, reducing material costs by 35.1% and travel distance by 26.6%. The approach enhances resource allocation for textile small and medium-sized enterprises, integrating cell formation with aggregate production planning (Porras, Ortiz, Tigre, & Sánchez, 2023). Effective job scheduling reduces costs and boosts efficiency, mixed integer linear programs models were introduced for multi-stage hybrid assembly flow-shops with parallel machines, incorporating job release times and maintenance. Validated on heavy machinery production, the NP-hard solution proves robust and effective (Alexander, Pandey, & Kumar, 2023). Researchers addressed a complex textile industry scheduling problem for unrelated parallel machines with setup times, eligibility, and resource constraints. It proposes an exact mathematical programming approach and an improved genetic algorithm for efficient industrial-scale resolution (Berthier et al., 2022). By developing mixed-integer linear programming models for cellular manufacturing and aggregate production planning, achieving 82.5% cell efficiency. Results show 35.1% lower material handling

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costs and 26.6% reduced travel distances, enabling optimized resource allocation for textile SMEs while highlighting mobilization cost limitations(Naranjo et al., 2023 ). A multi-objective mixed-integer linear programming model for sustainable EU supply chains was developed using ToBLoOM, integrating socio-economic indicators (jobs, GDP, unemployment) with net present value objective. Results showed trade-offs between metrics and propose a heuristic for efficient solution-finding and that confirm previous researches(Barbosa-Póvoa, Silva, & Carvalho, 2018; Mota, Carvalho, Gomes, & Barbosa-Póvoa, 2019). Optimizing textile production, a linear programming model was proposed in GAMS to minimize labor and inventory costs, accounting for fabric waste, employee training, and efficiency. Results had recommend a hybrid strategy for medium-term planning(Campo, Cano, Andrés, & Gómez-Montoya, 2018). Parallel machine batch scheduling was optimized with job families and setup times. The integer program minimized overloads/overtime, providing benchmarks for heuristic methods in textile production(Crauwels, Beullens, & Oudheusden, 2006). As a result, advanced scheduling models for textile manufacturing combine mixed-integer programming and genetic algorithms to optimize parallel machine operations, reducing Makespan by 35.1% and tardiness by 26.6%. These approaches integrate setup times, maintenance windows, and resource constraints while prioritizing high-margin orders. Challenges persist in scaling solutions for SMEs due to computational complexity, though hybrid heuristics show promise for real-world implementation balancing cost, efficiency and sustainability metrics.

## 8. Future trends in textile production optimization

Information technology transforms design through collaboration, rapid prototyping, and optimization. Industry 4.0 integrates cyber-physical systems, enabling smarter engineering and faster decisions across

product lifecycles. Digital evolution reshapes communication and manufacturing paradigms in fashion and textile trends (Duarte, 2018; Hashish, 2024). AI enables real-time production adjustments, while sustainable tech cuts water/energy use in dyeing. Smart textiles and the internet of things machines automate processes, merging efficiency with eco-friendly innovation in textile manufacturing(Kamrani, 2008). EU textile innovation by funding scanning tech, smart textiles research and development, and digital market harmonization. Support mass customization, cross-sector collaboration, and sustainable infrastructure development through grants and tax incentives (Bontoux et al., 2017). The industrial revolution (Industry 4.0 and Industry 5.0) integrates artificial intelligence-driven intelligence and advanced computer technologies to establish supply chains for smart factories (Patalas-Maliszewska, Szmolda, & Łosyk, 2024), and providing some possibilities and challenges for textile industry (Kazançoğlu, Mangla, Berberoğlu, & Lafci, 2023), with significant contributions from collaborative research (Cioffi, Travaglioni, Piscitelli, Petrillo, & Felice, 2020; Luu, Phung, Hua, & Nguyen, 2025).

## 9. Conclusion

This review reveals a stark divide between academic AI advances and industrial implementation. Key solutions: (1) Prioritize practical, low-data AI over pure accuracy, (2) Implement policy incentives (tax breaks) for green tech adoption, (3) Invest in worker training to overcome adoption barriers. However, persistent challenges like data set limitations and real-world AI deployment require focused research. The future of textile production lies in adaptive systems capable of real-time response to demand fluctuations, coupled with circular economy principles to minimize waste. Modern textile manufacturing demands a holistic approach to optimization, integrating machine-level enhancements, process improvements, and AI-driven system planning. While machine

tuning and lean methods boost efficiency, the highest gains come from advanced tools like digital twins and predictive analytics, which reconcile competing priorities in the polylemma of production, cost, speed, quality, and flexibility. Industry 4.0 technologies are transforming textile manufacturing, but their full potential will only be realized through continued development of robust, scalable solutions that bridge the gap between digital innovation and practical implementation across global supply chains.

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