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INTEGRATING ARTIFICIAL INTELLIGENCE AND TIME-SERIES FORECASTING FOR SMART TEXTILE PRODUCTION: TRENDS, CHALLENGES, AND OPPORTUNITIES IN THE INDUSTRY 4.0 ERA

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Abstract

The increasing complexity of textile manufacturing in the industry 4.0 era has intensified the need for forecasting systems that can adapt to dynamic demand patterns, interconnected production networks, and heterogeneous data environments. This article provides a comprehensive review of how Artificial Intelligence (AI) and time-series forecasting techniques are being integrated to enhance operational intelligence within smart textile production. It synthesizes the strengths and limitations of classical statistical models, modern machine-learning architectures, and emerging hybrid approaches that combine linear decomposition with nonlinear learning. The review highlights how interconnected data ecosystems enabled by IoT sensors, RFID tracking, MES/ERP systems, edge–cloud architectures, and digital twins form the backbone of real-time predictive capabilities in contemporary textile factories. In examining recent research and industrial applications, the study identifies key opportunities for sustainability alignment, adaptive learning, and autonomous decision support, alongside persistent challenges related to data quality, interoperability, computational demands, and SME adoption barriers. Finally, the article outlines actionable future directions, including reinforcement-learning-driven forecasting, federated learning, lightweight edge analytics, standardized benchmarks, and sustainability-aware predictive models. By consolidating methodological advances and practical considerations, this review offers a grounded roadmap for deploying intelligent, responsive, and resilient forecasting systems within the evolving landscape of smart textile manufacturing.

Keywords: Smart Textile Manufacturing**,** AI-Driven Time-Series Forecasting**,** Industry 4.0 and Digital Transformation**,** Hybrid Forecasting Models**,** IoT and Edge-Cloud Data Ecosystems

1. Introduction

1.1 Background of Textile Production and Forecasting

The textile sector is among the most dynamic and globally competitive manufacturing industries, characterized by pronounced seasonality, short product life cycles, and volatile consumer demand, factors that complicate planning and forecasting (Kačmáry & Lörincz, 2023; Lorente-Leyva et al., 2020). Precise production forecasting therefore underpins supply-demand alignment, resource optimization, inventory reduction, and on-time fulfillment; empirical and case studies in textile operations and just-in-time (JIT) systems show forecasting's centrality to operational and inventory efficiency (Ingle & Jasper, 2025; Ogunyankinnu et al., 2024).

Conventional time-series and econometric methods remain useful in stable contexts but frequently fail to track nonlinear, rapidly shifting patterns in modern textile production, motivating hybrid and AI-driven time-series approaches (Lorente-Leyva et al., 2020; Domenteanu et al., 2025; Balcı et al., 2022). As production networks grow in complexity, integrating suppliers, manufacturing, and distribution, data-driven forecasting powered by AI becomes strategic, enabling demand-aware scheduling, quality control, and reduced waste within Industry 4.0 smart-textile ecosystems (Ingle & Jasper, 2025; Ogunyankinnu et al., 2024).

1.2 Industry 4.0 and the Digital Transformation of Textile Manufacturing

Industry 4.0 frames a systemic digital transformation in manufacturing by coupling automation, interconnectivity, and data-driven intelligence. Systematic reviews emphasize how cyber-physical systems (CPS), artificial intelligence (AI), the Internet of Things (IoT), and real-time analytics create transparency and enhance sustainable production planning capabilities across sectors (Kashpruk et al., 2023). In textiles specifically, case studies and applied research show smart factories deploying IoT sensors, edge-cloud telemetry, and CPS to track machine health, material flow, and energy consumption, thereby converting raw sensor streams into operational insight for shop-floor control and sustainability metrics (Nwamekwe & Nwabunwanne, 2025).

This infrastructural shift moves firms from reactive fixes toward predictive and prescriptive operations: IoT-enabled telemetry combined with time-series forecasting and AI facilitates early detection of demand surges, anomaly-driven maintenance scheduling, and energy optimization, ultimately improving uptime and resource efficiency in textile plants (Nwamekwe et al., 2020). Edge-cloud architectures and hybrid forecasting frameworks thus become central enablers of Industry 4.0 objectives for resilient, low-waste smart textile production (Nwamekwe & Chikwendu, 2025; Nwamekwe & Nwabunwanne, 2025).

1.3 Rationale and Objectives of the Review

While numerous studies have advanced either AI applications or time-series forecasting in textiles, integrated investigations that systematically marry these approaches remain limited. Reviews and bibliometric analyses document rapid growth in AI and forecasting research but note gaps in end-to-end industrial integration (Nwamekwe et al., 2025; Wang et al., 2023), and only isolated hybrid examples exist (e.g., time-series imaging, knowledge-graph/time-series fusion, production-fault forecasting) that illustrate potential but not widespread adoption (Seçkin et al., 2019). These asymmetries motivate a focused synthesis that moves beyond method papers to show how hybrids perform in real factory contexts (Nwamekwe et al., 2025; Wang et al., 2023).

This review therefore aims to (i) map recent hybrid AI–time-series frameworks and their industrial deployments, (ii) identify operational, data, and energy-sustainability trade-offs exposed in practice, and (iii) propose benchmarking and standardization pathways for scalable Industry 4.0 adoption (Malashin et al., 2025; Nwamekwe et al., 2025; Nwamekwe et al., 2024). By collating evidence across methodological innovations and lifecycle-oriented needs, the review seeks actionable guidance for improving predictive performance, enabling zero-defect and green production, and aligning smart textile systems with Industry 4.0 imperatives (Nwamekwe et al., 2024).

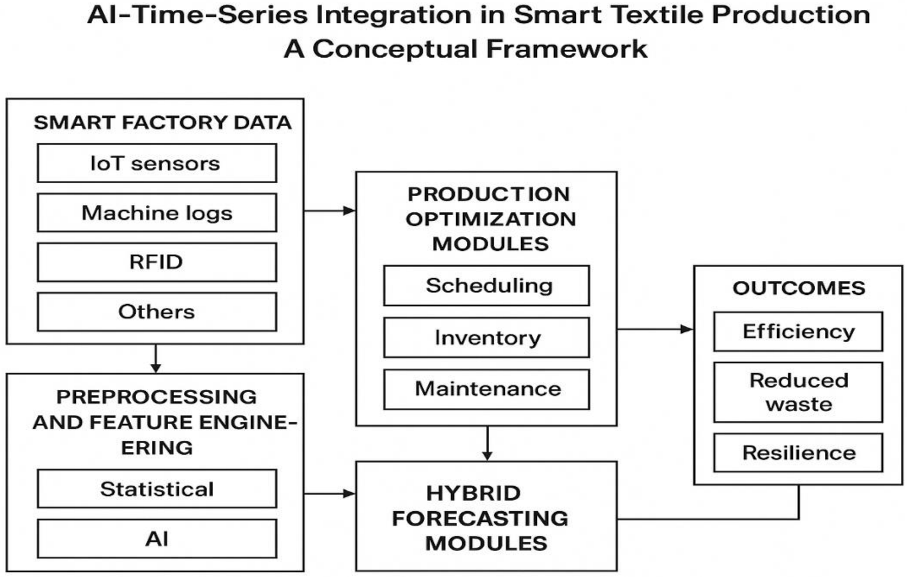

Figure 1: Conceptual Framework of AI + Time-Series Forecasting

The conceptual framework in Figure 1 outlines how artificial intelligence and time-series forecasting function within a smart textile production system. It illustrates the flow of real-time factory data through stages such as acquisition, preprocessing, forecasting, and production optimization. The diagram shows the interactions among IoT sensors, feature engineering, hybrid forecasting models, and operational activities like scheduling, inventory, and maintenance. This structure clarifies how textile factories shift from reactive to predictive systems. It also highlights key outcomes, improved efficiency, reduced waste, and stronger production resilience, helping readers visualize the transformative impact of AI-driven automation in modern textile operations.

2. Theoretical Foundations of Forecasting Models

2.1 Classical Time-Series Forecasting Approaches

Classical forecasting techniques which are ARIMA, SARIMA, and exponential smoothing (ETS/Holt variants), remain foundational for demand prediction, inventory control, and production scheduling because they explicitly model temporal dependence and seasonality from historical data (Nwamekwe & Igbokwe, 2024; Seçkin et al., 2019). In industrial and textile case studies, these methods are practical where demand and production follow regular seasonal cycles or relatively stable trends: ARIMA/SARIMA formulations are designed to capture lagged correlations and periodic components commonly observed in yarn and fabric demand data (Seçkin et al., 2019).

However, these methods often assume linear relationships and may struggle to represent complex, nonlinear interactions or cross-series dependencies that arise in multifactorial supply chains and dynamic market conditions, limiting forecast accuracy in modern textile settings. Consequently, recent research advocates for hybrid and global-learning frameworks such as integrating ARIMA/ETS with deep learning or pooled global representations, to maintain statistical robustness for seasonality while capturing nonlinear dynamics and cross-series signals (Nwamekwe et al., 2025).

2.2 Artificial Intelligence and Machine Learning Approaches

Artificial intelligence (AI) and machine learning (ML) approaches have rapidly become powerful alternatives to classical time series methods because they natively represent nonlinear functions, learn high dimensional interactions, and model complex temporal dependencies from heterogeneous industrial data (Giri et al., 2019; Nwamekwe et al., 2025; Malashin et al., 2025). Common supervised learners, such as artificial neural networks, support-vector regression, and random forests, alongside recurrent/deep sequence architectures like LSTM, GRU, and Transformer-based models, have been applied to forecasting tasks in manufacturing and specifically in textile problems. These techniques can effectively capture nonlinearity, long-range temporal correlations, and cross-series information that traditional linear models often miss (Giri et al., 2019; Nwamekwe et al., 2025; Kashpruk et al., 2023). Empirical textile-domain examples illustrate these strengths: LSTM based and other deep sequence models have been used successfully for energy and production-rate prediction and for reducing overconsumption in textile plants, demonstrating improved temporal generalization relative to baseline methods (Emeka et al., 2025).

Beyond raw forecasting accuracy, AI/ML methods excel at integrating unstructured and multi-modal factory data, including sensor telemetry, machine logs, visual inspections, and sales histories, enabling unified predictive pipelines for quality control, predictive maintenance, and demand planning (Nwamekwe et al., 2025). Hybrid and ensemble strategies that combine statistical seasonality models with global deep representations or physics-aware modules further improve robustness across different forecasting horizons and non-stationary regimes common in textiles (Kashpruk et al., 2023; Emeka et al., 2025); in practice, these data-driven systems have been deployed to enhance inventory accuracy and sales prediction in industrial field studies and small textile firms, showing measurable operational gains when coupled with insights from process engineering (Okeagu et al., 2024). Widespread industrial adoption nevertheless requires interdisciplinary collaboration, standardized benchmarking, and careful consideration of energy and deployment trade-offs to ensure that AI forecasting scales responsibly within Industry 4.0 textile ecosystems (Malashin et al., 2025; Nwamekwe et al., 2025).

2.3 Comparative Strengths and Limitations

Classical statistical time series methods retain distinct advantages in textile forecasting because they are conceptually simple, interpretable by domain experts, and computationally efficient for short to medium horizon problems where seasonal cycles

and trend components dominate (Kačmáry & Lörincz, 2023; Seçkin et al., 2019; Lorente-Leyva et al., 2020). Reviews and methodological comparisons show that ARIMA/SARIMA and exponential smoothing families remain attractive for operational uses inventory rules, rolling production schedules and baseline demand projections precisely because model structure maps directly to familiar notions of trend, seasonality and residual variability and can be implemented with modest data and compute budgets (Kačmáry & Lörincz, 2023; Seçkin et al., 2019; Lorente-Leyva et al., 2020). At the same time, these approaches are constrained by linearity assumptions and limited capacity to exploit cross series information or heterogeneous factory signals (e.g., multi sensor telemetry, visual inspection outputs) that increasingly characterize Industry 4.0 textile data; empirical and review studies therefore highlight that pure statistical models can be brittle under nonstationarity and multivariate interdependence common in contemporary production systems (Lorente-Leyva et al., 2020; Domenteanu et al., 2025; Balcı et al., 2022).
AI and modern ML architectures offer complementary strengths: recurrent and attention based deep models capture nonlinear dependencies, long range temporal structure and multi modal inputs, making them well suited to forecasting problems driven by complex interactions among sales, operations and machine health streams (Ingle & Jasper, 2025; Wang et al., 2023). However, these gains come with practical costs, deep and ensemble models typically demand larger labelled datasets, careful hyperparameter tuning, greater computational resources and mindful deployment to avoid excessive energy use or overfitting in small data contexts (Kačmáry & Lörincz, 2023; Balcı et al., 2022; Nwamekwe et al., 2025; Wang et al., 2023). Because of the trade offs between transparency and expressive power, recent literature and competition results point to hybrid strategies (statistical layering, residual modelling, or ensemble/meta learning) as the pragmatic pathway: hybrids preserve the interpretability and seasonality guarantees of classical models while leveraging AI to capture residual nonlinearity and cross series signals, yielding robust gains in industrial forecasting performance when designed and validated appropriately (Ogunyankinnu et al., 2024; Lorente-Leyva et al., 2020; Domenteanu et al., 2025).

	Classical	AI-Based	Hybrid
Strengths	Simple	High performance	Balanced
Limitations	Linear	Black-box	Complex
Data Needs	Low	High	Variable
Industrial Fit	High	Medium	High
Nonlinearity	Limited	High	High
Cost	Low	High	Medium

Figure 2: Comparison Matrix: Classical vs AI vs Hybrid Forecasting Models

The comparison matrix presented in Figure 2 visually summarizes the differences among classical, AI-based, and hybrid forecasting models in terms of strength, limitations, data requirements, and industrial applicability. This visual simplifies the dense narrative in the forecasting literature by contrasting the linear and interpretable nature of classical models with the adaptability and nonlinear modelling capabilities of AI-based approaches. It also highlights the balanced performance of hybrid models, which leverage the advantages of both families. The table helps readers quickly discern which modelling paradigm is most suitable for different levels of data availability, computational capacity, and real-world implementation in textile production.

3. Integration of AI and Time-Series Forecasting in Textile Manufacturing

3.1 Hybrid and Ensemble Forecasting Frameworks

Hybrid forecasting frameworks explicitly combine the interpretability and seasonality-capture of statistical decompositions with the nonlinear learning capacity of machine learning models, and this serial or parallel coupling has become a practical standard in many time series applications (Kačmáry & Lörincz, 2023; Lorente-Leyva et al., 2020; Malashin et al., 2025). Typical architectures like ARIMA-ANN, ARIMA-LSTM and CNN-LSTM hybrids, first extract linear and seasonal components with a traditional model (e.g., ARIMA/SARIMA or decomposition) and then let a neural network learn the remaining nonlinear residuals; empirical studies across domains demonstrate that this decomposition-plus residual approach improves accuracy and robustness versus standalone methods (Kačmáry & Lörincz, 2023; Lorente-Leyva et al., 2020; Ogunyankinnu et al., 2024; Malashin et al., 2025). Textile focused reviews and surveys further confirm the migration of these hybrid patterns into fabric and process analytics, where deep architectures (including CNNs for image-based quality signals and LSTMs/GRUs for sequence data) are fused with statistical baselines to model complex interactions among demand, machine telemetry and process parameters (Domenteanu et al., 2025; Malashin et al., 2025; Nwamekwe et al., 2024).

Ensemble strategies which are stacking, boosting and meta learning, extend the hybrid idea by blending diverse model families to reduce variance and increase stability across nonstationary manufacturing series; meta forecasting and global representation work show that such ensembles can generalize better across many related production time series common in textile operations (Nwamekwe et al., 2025; Malashin et al., 2025; Nwamekwe et al., 2024). Practical textile applications already reported in the literature include production fault prediction in glove manufacturing, demand and inventory forecasting for JIT replenishment, and integrated bottleneck analysis using knowledge graph/time series hybrids, all of which report improved operational indicators (e.g., lower error, earlier anomaly detection, more stable schedules) when hybrid or ensemble pipelines are deployed (Balcı et al., 2022; Nwamekwe et al., 2025; Wang et al., 2023; Seçkin et al., 2019). Taken together, these results indicate that hybrid and ensemble frameworks offer a pragmatic pathway for smart textile plants to retain the transparency of classical methods while capturing the nonlinear, multi modal dynamics introduced by Industry 4.0 sensors and processes (Domenteanu et al., 2025; Malashin et al., 2025; Nwamekwe et al., 2024).

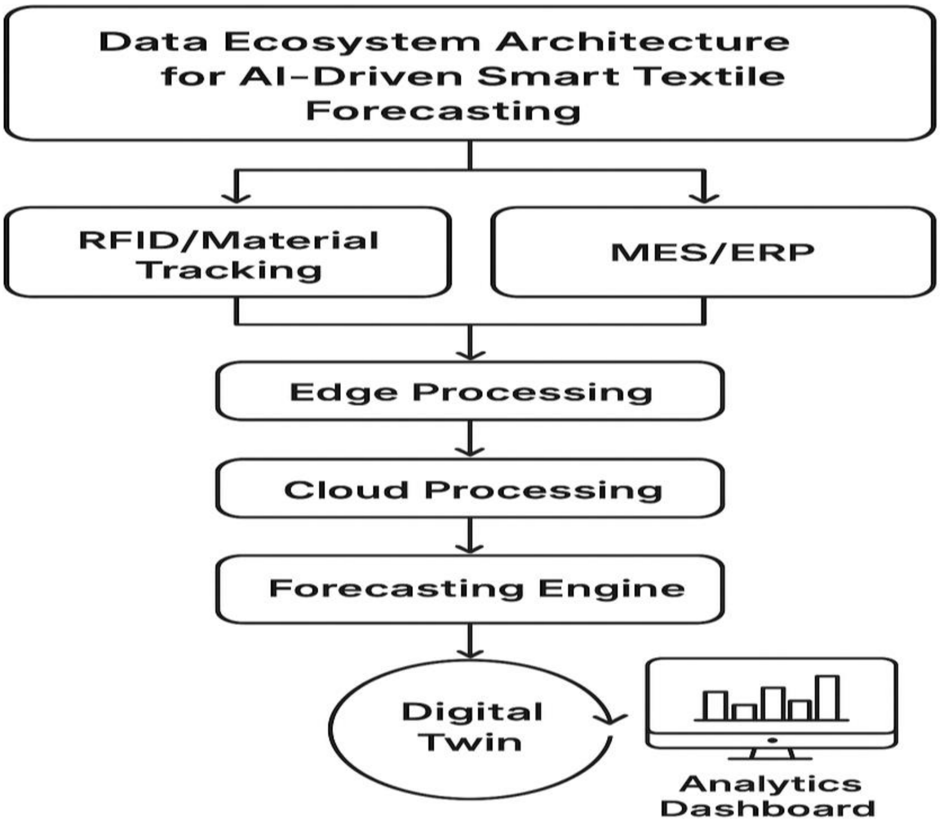

Figure 3: Data Ecosystem Architecture for AI-Driven Smart Textile Forecasting

Figure 3 depicts the end-to-end data infrastructure underpinning forecasting in Industry 4.0 textile environments. It shows how IoT devices, RFID tracking, and MES/ERP systems feed into edge and cloud processing layers that support advanced forecasting engines.

The inclusion of a digital twin emphasizes the role of real-time feedback loops in refining predictions and optimizing operations. Overall, the visual helps readers understand how multiple data streams integrate to enable predictive maintenance, demand forecasting, and production scheduling.

3.2 Smart Factory Data Ecosystems

Smart textile plants now form dense, real-time data ecosystems as low-cost sensors and embedded IoT nodes continuously record temperature, vibration, energy use, and other process variables across spinning, weaving, and finishing lines. Material-tracking technologies such as RFID and supervisory control layers link shop-floor telemetry to MES/ERP records, while stream platforms and cloud services enable scalable ingestion and preprocessing for downstream analytics (Durdu et al., 2019). These architectures often augmented by digital twins, provide the infrastructural substrate needed to convert raw telemetry into actionable intelligence for production control and scheduling (Igbokwe et al., 2025).

When fused, multi-source streams (machine sensors, historical production logs, market/demand feeds) materially improve predictive maintenance, anomaly detection, and short-horizon production forecasts: graph- and deep-learning methods applied to Industrial Internet of Things (IIoT) data have already demonstrated enhanced fault detection and reduced downtime in industrial settings (U-Dominic et al., 2025). Nevertheless, practitioners must address data quality, interoperability, and governance challenges to realize robust, real-time forecasting in Industry 4.0 textile environments (Nwamekwe et al., 2025).

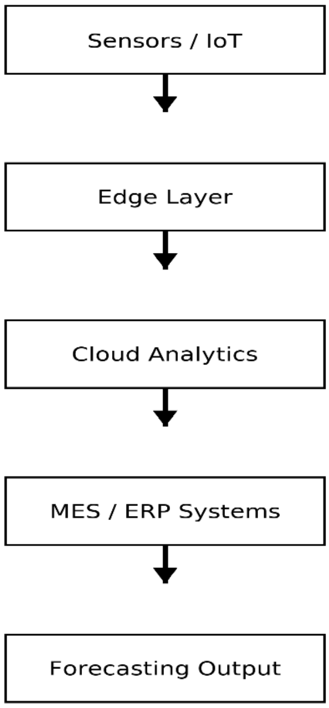

Figure 4: Smart Factory Data Ecosystem Diagram

The ecosystem diagram in Figure 4 illustrates the layered data architecture that enables intelligent textile manufacturing under Industry 4.0. It depicts how information flows from

IoT sensors to the edge layer, then to cloud analytics, and finally into enterprise-level systems such as MES and ERP platforms. This stepwise arrangement clarifies the progression from raw data collection to actionable forecasting outputs. By showing this vertical data pipeline, the visual reinforces the importance of distributed computing and real-time responsiveness in modern textile factories. It helps readers appreciate how forecasting models depend on coordinated data flows across multiple architectural layers.

3.3 Case Studies and Recent Research Applications

Hybrid AI-time-series architectures serial decompositions (e.g., ARIMA→ANN/LSTM) and joint CNN-RNN hybrids, have been shown to combine statistical seasonality capture with nonlinear residual learning, producing more robust forecasts in textile contexts such as sales and fault-rate prediction. Empirical work in textiles and method reviews report that these hybrids reduce forecast error and improve anomaly detection compared to single model baselines by leveraging decomposition for linear structure and deep learning methods for complex residuals.

Industry case studies confirm practical gains when hybrid models are embedded into enterprise workflows: small and regional textile firms applying machine learning-augmented forecasting and ERP integration report improved responsiveness to demand fluctuations and fewer stock imbalances; parallel work in South Asian and European clusters highlights predictive maintenance and energy efficiency benefits from AI time-series pipelines in smart plants.

4. Emerging Trends, Challenges, and Research Gaps

4.1 Emerging Trends in Smart Textile Forecasting

Recent advances in forecasting exploit attention and graph architectures to model multidimensional, interconnected production data: Transformer-style attention mechanisms and spatial-temporal graph neural networks (GNNs) now support forecasting across linked machines and production stages, improving representation of cross-series dependencies and irregular temporal patterns (Chidiebube et al., 2025). Parallel to model innovation, Digital Twins and digital twin manufacturing ecosystems are being adopted in textiles to simulate process dynamics, validate forecasting hypotheses, and tighten the loop between virtual experiments and shop-floor data, thereby raising forecast fidelity for complex operations such as dyeing and finishing (Chidiebube et al., 2025).

Concurrently, the cloud-edge continuum and lightweight edge analytics make real-time prediction feasible on the factory floor, reducing latency and data transfer while enabling timely prescriptive actions; hybrid edge-cloud deployments have shown substantial reductions in bandwidth and improved responsiveness for IIoT analytics (Nwamekwe & Chikwendu, 2025; Mohsin et al., 2024). Reinforcement learning and adaptive control methods are increasingly explored to convert forecasts into self-tuning schedules and energy-aware control policies, demonstrating promising gains in operational adaptivity and efficiency in recent experimental studies (Jiang, 2022).

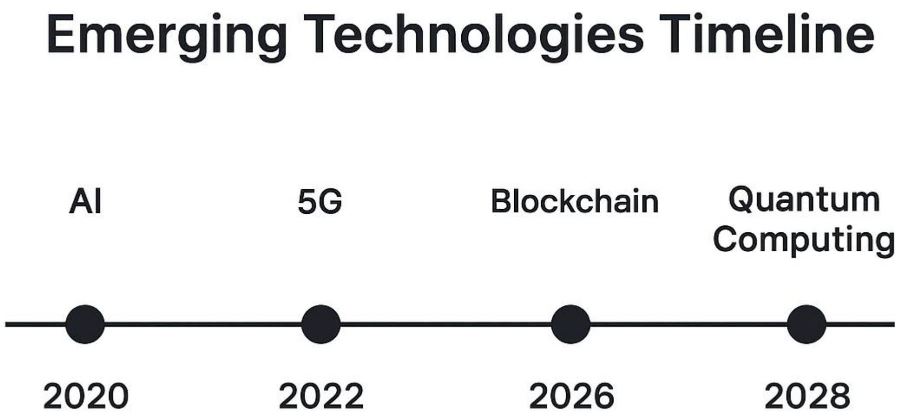

Figure 5: Emerging Technologies Timeline

The timeline in figure 5 illustrates the chronological progression of key technological advancements influencing modern forecasting, including AI-driven innovations, connectivity improvements, and advanced computation. By placing these technologies along a temporal axis, the visual conveys how forecasting capabilities have evolved and where the industry is heading. It highlights the accelerating pace of innovation and helps situate current research trends within a broader technological context.

4.2 Key Challenges and Limitations

Despite notable advances, smart-textile forecasting faces persistent data and systems barriers: high-quality labelled datasets are scarce, and missing or irregular annotations constrain ML generalization and supervised training regimes (Dwivedi et al., 2021). Sensor noise, heterogeneous sampling rates and formats across facilities degrade model consistency and complicate transferability between plants (Nwamekwe et al., 2024). At the systems level, retrofitting legacy textile machinery into modern IIoT stacks remains a technical bottleneck, poor interoperability and fragmented control layers hinder unified data ingestion and real-time inference (Nwamekwe et al., 2024).

Operationalizing AI hybrids adds further limits: deep models often behave as “black boxes,” reducing operator trust and complicating root-cause analysis for forecasts and prescriptive actions (Dwivedi et al., 2021; Malashin et al., 2025). Training and maintaining large hybrid networks impose substantial computational and energy costs that many small and medium-sized enterprises (SMEs) cannot sustain, motivating lightweight architectures, model compression, and edge-aware designs to balance performance, cost, and deployability (Mahmood et al., 2022).

4.3 Identified Research Gaps

Despite growing methodical advances, key gaps hinder the deployment of AI forecasting in textile plants: there is no widely adopted, standardized MLOps/operational framework for integrating forecasting models into shop-floor control and ERP/MES pipelines, limiting reproducibility and enterprise uptake (Okpala et al., 2024; Ingle & Jasper, 2025). High-quality, large-scale industrial time series remain scarce in textiles, heterogeneous materials and process variability impede labelled dataset assembly and transfer learning, so probabilistic, multi-series methods that require pooled data (like DeepAR) cannot reach their full potential without open industrial datasets and benchmark suites (Malashin et al., 2025; Vitalis et al., 2024).

Research also under-investigates multi-objective forecasting that jointly trades accuracy, energy footprint, and sustainability metrics: cloud/edge energy costs and deployment trade-offs call for methods that optimize accuracy while minimizing computational and carbon budgets and for embedding circularity indicators (waste, reuse rates) into objective functions (Onyeka et al., 2024; Riba et al., 2022). Finally, few-shot and meta-learning strategies to enable SME adoption with limited data are promising but underexplored; open datasets, standardized benchmarks, and cross-disciplinary protocols remain urgent priorities (Ezeanyim et al., 2025).

5. Opportunities and Future Directions

5.1 Integration with Sustainable Manufacturing Goals (Industry 5.0 Perspective)

As manufacturing shifts toward an Industry 5.0 ethos prioritizing human-machine collaboration and socio ecological goals integrating AI forecasting with sustainability metrics becomes essential for textile firms to reduce waste, optimize energy use, and incorporate circular-economy objectives into production planning (Malashin et al., 2025; Okpala et al., 2025). Reviews of AI applications in technical textiles indicate that predictive models can automate process control and maintenance, thus promoting resource-efficient operations; concurrently, studies on circularity emphasize that demand-aware scheduling and targeted recycling can minimize landfill contributions and resource consumption in apparel value chains (Malashin et al., 2025; Okpala et al., 2025).

In practice, sustainability-aware forecasting aligns ecological objectives (e.g., emissions and energy budgets) with traditional accuracy metrics: digital twins and IIoT platforms can simulate scenarios and validate eco constrained production schedules, while dynamic carbon and energy predictors allow for energy-efficient dispatching to reduce operational footprints (Igbokwe et al., 2024). Emerging trends in Generative AI (GenAI) and advanced optimization can facilitate the adjustment of forecasts to accommodate multiple objectives (accuracy, energy efficiency, waste reduction), yet their widespread adoption necessitates the development of cross-disciplinary standards and user-friendly approaches for small and medium-sized enterprises to implement.

5.2 Towards Self-Learning and Adaptive Forecasting Systems

The evolution of smart textile production is steadily moving toward forecasting systems that can learn and adapt on their own, even as factory conditions change. Instead of relying on manual updates or periodic model retraining, next-generation systems will continuously refine their predictions based on real-time feedback from the production floor. Reinforcement learning, for example, enables forecasting models to improve through trial and error, learning which decisions lead to better outcomes in scheduling, inventory planning, or machine utilization. Transfer learning will also play a crucial role by allowing knowledge gained in one textile environment to be applied across other plants. This means a model trained on one production line can quickly adapt to another with minimal additional data, reducing development costs and speeding up deployment. At the same time, federated learning offers a pathway for collaborative intelligence across distributed textile facilities while maintaining strict data privacy. Each plant can contribute to a shared global model without exposing sensitive operational information. The growing integration of edge computing and real-time analytics further strengthens the adaptability of these systems. By processing data closer to the machines, forecasts can be updated instantly in response to sudden disruptions, demand shifts, or changes in material availability. This immediacy supports agile decision-making, enabling manufacturers to coordinate production more efficiently across supply chains. Ultimately, the shift toward self-learning and adaptive forecasting systems promises a more responsive, resilient, and intelligent textile manufacturing ecosystem aligned with the goals of Industry 4.0. and global supply chain coordination.

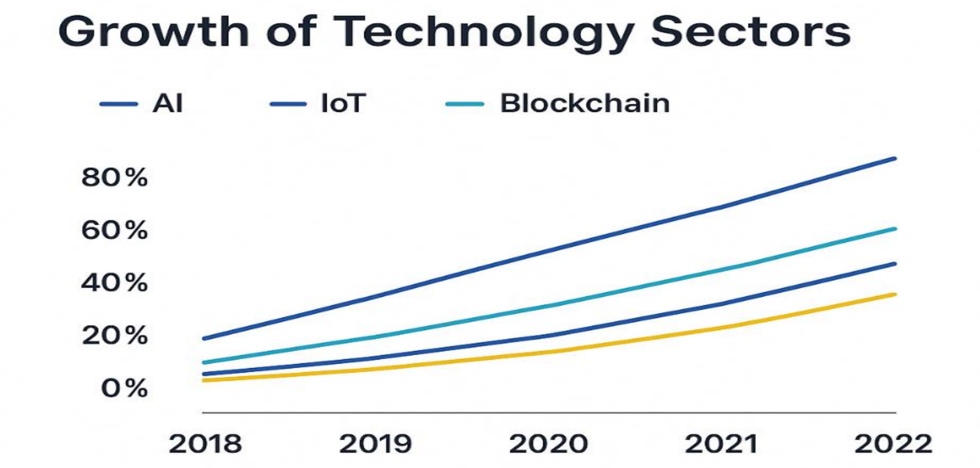

Figure 6: Growth of Technology Sectors (Reinforcing Trend Context)

Figure 6 presents the rising influence of major digital technologies such as including AI, IoT, and blockchain, over a recent five-year period. By depicting growth trajectories, it reinforces the manuscript's argument that advances in data-driven and connected technologies are steadily reshaping manufacturing forecasting. Although not domain-specific, the graph provides helpful macro-context that supports discussions in Sections 1 and 4, where broader industrial digitalization trends are referenced. The visual helps readers appreciate the momentum behind enabling technologies and implicitly, the increasing relevance of AI-enhanced forecasting for modern textile production.

6. Conclusion

The synthesis presented in this review demonstrates that the convergence of Artificial Intelligence and time-series forecasting is redefining what is possible in textile production systems as they transition toward fully realized Industry 4.0 environments. Classical forecasting models are robust, transparent, and well-suited for stable seasonal patterns but are increasingly insufficient for the nonlinear, multivariate, and rapidly shifting dynamics characteristic of modern textile operations. AI and machine learning models, especially deep sequence architectures and hybrid ensembles, address many of these limitations by capturing complex temporal structures, integrating heterogeneous data streams, and supporting predictive tasks that extend beyond traditional demand forecasting. Across the literature, hybrid approaches that blend statistical decomposition with nonlinear learning consistently emerge as the most practical and effective pathway, balancing interpretability with adaptive intelligence. Complementing these methodological developments, textile factories are evolving into deeply interconnected data ecosystems where IoT sensors, RFID systems, MES/ERP platforms, edge–cloud pipelines, and digital twins collectively shape the conditions for real-time forecasting and decision making. Yet, the review also highlights persistent challenges, including fragmented data infrastructures, limited large-scale industrial datasets, computational burdens, and the need for domain-aligned benchmark standards that can guide responsible and scalable deployment.

Looking ahead, the trajectory of smart textile production suggests that future breakthroughs will depend on designing forecasting systems that not only predict accurately but also adapt autonomously and support broader organizational goals such as sustainability, resilience, and energy efficiency. Emerging directions could be reinforcement learning for self-optimizing schedules, federated learning for privacy-preserving collaboration across distributed plants, and edge-enabled real-time analytics, collectively point toward a new generation of self-learning, context-aware forecasting engines capable of responding dynamically to operational uncertainties. At the same time, the shift toward Industry 5.0 underscores the importance of harmonizing these technological capabilities with human-centric and ecological considerations. Integrating sustainability metrics into forecasting pipelines, leveraging digital twins for scenario evaluation, and adopting lightweight, SME-friendly AI architectures will be essential for ensuring equitable uptake across different scales of textile production. Ultimately, the future of forecasting in textiles lies in building holistic and interoperable digital ecosystems, where data, algorithms, infrastructure, and human expertise align to support intelligent, low-waste, and resilient manufacturing. This review provides a grounded foundation for guiding that evolution and highlights the critical avenues where research, industry, and policy must converge to fully realize the promise of AI-enhanced forecasting in the textile sector.

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