AI-Driven Transformation in the Textile Industry: A Bibliometric Analysis and Scoping Review

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Abstract. Artificial Intelligence (AI) is rapidly reshaping the global textile industry, driving efficiency, precision, and sustainability across its value chain. Yet despite growing enthusiasm, the integration of AI remains fragmented, with limited statistical understanding of where, how, and why these technologies take root. This study addresses that gap by combining bibliometric network analysis and systematic scoping review to map and statistically interpret two decades (2003–2023) of research on AI applications in textiles. Using association strength normalization, VOS modularity clustering, and thematic centrality density mapping, we identified eight manufacturing clusters ranging from fabric defect detection and supply chain optimization to textile waste management and sustainability that structure the field. The novelty of this work lies in repositioning bibliometric analysis as a statistical instrument, not merely a descriptive tool. Keyword co-occurrence networks and citation trajectories are translated into evidence-based research agendas, connecting cluster signals to methodological pathways such as regression modeling, support vector machines, neural networks, and hybrid ML-statistical frameworks. This statistical logic is used to surface gaps. Particularly in empirical validation, predictive modeling, and cross-cluster integration and to chart future directions for data-driven textile innovation. By grounding future agendas in measurable statistical patterns rather than narrative interpretation alone, this study offers a rigorous analytical framework that links research structure to methodological opportunity. The resulting roadmap invites scholars and practitioners to bridge AI, textile engineering, and applied statistics, shifting the field from fragmented experimentation toward coherent, evidence-based innovation.

Keyword: Artificial Intelligence, Textile Industry, Bibliometric Analysis, Machine Learning, Statistical Modeling, Scoping Review.

1. Introduction

The condition of textiles in Indonesia has begun to focus on sustainability issues [1]. The textile industry worldwide is also improving, with advancements in waste minimization [2] and digitalization [3]. This is both an opportunity and a challenge for the textile industry, especially in Indonesia's textile sector.

The textile industry worldwide has been shifting its focus towards sustainability issues [4], including efforts to minimize textile waste [2] and adopt digitalization [3]. Indonesia's textile industry has also begun to focus on sustainability issues [1]. The government has mandated the "Making Indonesia 4.0" roadmap, with a strategic emphasis on integrating Industry 4.0 technologies to enhance global competitiveness and productivity [5]. The initiative prioritizes technological innovations, such as automation, IoT, and data analytics, to streamline manufacturing processes, reduce waste, and enhance product quality, thereby positioning Indonesia as a leader in the global textile and apparel industry [5]. In achieving this goal, the technological approach is no longer inevitable and has become an integral part of the manufacturing industry in Indonesia [1], [6].

However, technology has disrupted part of the manufacturing process, forcing several companies to adjust and collaborate to solve these technological challenges [6]. Several technologies are employed to enhance productivity and quality, leveraging the latest advancements, such as artificial intelligence [7], [8], [9], [10], [11]. Other technologies, such as automation [12], [13], [14] machine learning [15], [16], [17] and smart manufacturing [18], [19] can help the manufacturing industry, especially the Indonesian textile industry, in accelerating the implementation of technology and competing globally.

According to [21], [22] technological developments will have a positive long-term impact on the manufacturing industry, particularly the textile industry in Indonesia, enabling significant increases in production and product quality, and maintaining its competitiveness in a global market [23]. Thus, appropriate investments in technology [24], [25] can significantly increase Indonesia's textile industry productivity. Automation and smart manufacturing systems will optimize production processes, reduce human error, and improve efficiency [14], [26], [27]. Additionally, technology will enable the enhancement of product quality, compliance with international standards, and expansion of market share. Furthermore, technological advancements are essential for fostering sustainability in the textile industry. Integrating sustainable innovations, such as eco-design and waste management practices, can significantly reduce the environmental impact of production [28]. In addition, the adoption of circular fashion principles and bio-based materials, as highlighted by [29], enables the textile industry to minimize waste, reduce resource consumption, and meet the growing demand for eco-friendly products. By investing in these sustainable technologies, Indonesia's textile industry can enhance its international competitiveness, attract environmentally conscious consumers, and support its long-term environmental goals.

Artificial intelligence (AI) is increasingly embedded across textile processes from surface modification and fiber control to yarn property prediction, offering tangible gains in efficiency, quality, and sustainability (Abd Jelil et al., 2013; Almonti et al., 2019; El-Geiheini et al., 2020). Prior work largely describes the promise of automation, AI, and machine learning in manufacturing (Ding et al., 2020a; Jbair et al., 2022; Lee, 2023), yet implementation pathways specific to the textile industry remain underdeveloped. To address this gap, a bibliometric approach can systematically surface trends, influential contributors, and technology domains most likely to translate into practice (Pitt et al., 2021). Such evidence helps researchers and decision makers identify effective technologies and chart feasible adoption routes, while also informing strategic investment choices aimed at productivity, quality, and sustainability gains.

At the market level, the global textile and apparel value chain is projected to grow about 5% annually to reach US$2.1 trillion by 2025 (Lu, 2015). Country anchors illustrate the sector's macroeconomic weight: in India, textiles contribute approximately 4% to GDP and employ roughly 45 million people, the second-largest employer after agriculture, while remaining a critical source of export earnings (Mukherjee & Chanda, 2016; Poonkuzhali & Vinodhkumar, 2019). Pakistan shows a similar pattern, with textiles accounting for around 8.5% of GDP ("Making export of textile globally competitive," 2007). For researchers and investors, these profiles are directional signals: a targeted bibliometric lens can reveal which technology themes are accelerating (e.g., AI-enabled defect detection, wastewater treatment, supply-chain analytics), who the influential authors and institutions are, and where collaboration networks already exist, thus lowering search costs and de-risking capital allocation (Lu, 2015; Mukherjee & Chanda, 2016; Poonkuzhali & Vinodhkumar, 2019; "Making export of textile globally competitive," 2007). Taken together, the scale of the market and the concentration of capabilities motivate a systematic mapping of the AI research landscape to inform feasible implementation pathways.

Therefore, this study aims to map the development of AI-related research in the textile industry through an integrative bibliometric and scoping review, in order to identify key trends, gaps, and strategic directions for future implementation.

2. Research Method

To strengthen the analytical depth, this study integrates bibliometric analysis and systematic literature review (SLR) in a complementary workflow. The bibliometric analysis was performed using Bibliometrix (R) and VOSviewer, focusing on both descriptive indicators (e.g., publication trends, source impact, h-index) and network-based indicators (e.g., co-authorship networks, keyword co-occurrence, and citation linkages). The data collection followed a structured PRISMA approach, as shown in figure 1, with an expanded Boolean search strategy and topic refinement to ensure comprehensive coverage of AI-related research in textiles. The SLR component adds interpretive depth by validating the keyword clusters produced during bibliometric mapping and identifying practical applications of AI, such as defect detection, process automation, sustainability, and smart textiles, within the most influential publications. [40], [41], [42], [43].

Statistically, the keyword co-occurrence networks were generated using association strength normalization with a minimum occurrence threshold of 5, and clustering was performed using the VOS modularity algorithm (resolution = 1.00). To test cluster robustness, sensitivity analyses were conducted by varying keyword thresholds (3–8 occurrences). Centrality and density measures were applied to interpret network structures and thematic evolution. Data quality was ensured through a multi-step screening process: duplicate removal by DOI/EID matching, restriction to peer-reviewed articles (2003–2025), language filtering (English only), and manual validation of top authors and keywords. This integrated bibliometric–SLR approach allows for both quantitative mapping of research structures and qualitative synthesis of thematic areas, ensuring methodological transparency and analytical rigor.

A step-by-step approach in this study has been carried out by previous research [44] using bibliometric analysis with five stages: (1) Research design, (2) Data collection, (3) Analysis, (4) Visualization, and (5) Interpretation [44].

The research will begin by carrying out a series of steps in bibliometric analysis, as shown in table 1 below:

Table 1. Bibliometric Step for Analysis

Step 1	Defining the area of research	Implementation of Artificial Intelligence in the Textile Industry
Step 2	Database Selection	Scopus database
Step 3	Search parameter for the field	Keywords: (1) “(TITLE-ABS-KEY (artificial* OR intelligence*) AND TITLE-ABS-KEY (textile* AND industr*)) AND PUBYEAR > 2002 AND PUBYEAR < 2024 AND (LIMIT-TO (DOCTYPE, "ar"))”
Step 4	Time period	(1) 2003-2023
Step 5	Tools for analysis	Bibliometrix R package, PRISMA, VoS Viewer
Step 6	Examination of information	Report, analysis, and discussion of results

By following this series of steps, this study aims to investigate and elaborate on the development of research on implementing artificial intelligence in the textile industry over a specified period. This bibliometric analysis will provide valuable insights into research trends, scientific collaborations, and developments in this area.

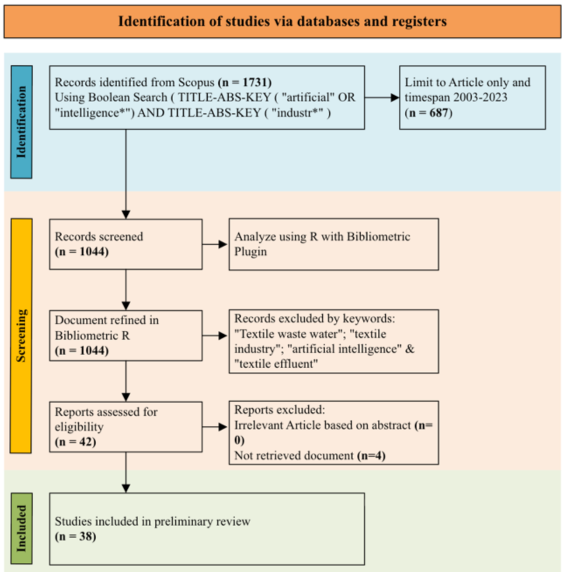

Figure 1. Data search flow combined PRISMA

Figure 1 describes the suitable articles based on the results of the following screening. A total of 38 articles can be downloaded in the full paper. In contrast, four articles cannot be downloaded, so the analysis of articles about Artificial Intelligence in the Textile Industry is limited to the 38 *extracted* articles. An in-depth Systematic Literature Review (SLR) is used in this section to obtain information on the discipline and the potential practical and theoretical use of AI in the future. Using SLR, authors can provide in-depth mapping through systematic analysis of the entire article.

3. Result and Discussion

A more in-depth analysis was conducted to examine the development and trends in research on this topic.

Table 2. Annual Scientific Production

Year	Articles	Year	Article	Year	Articles
2003	32	2010	40	2017	38
2004	63	2011	37	2018	41
2005	50	2012	37	2019	46
2006	50	2013	30	2020	64
2007	57	2014	34	2021	78
2008	45	2015	34	2022	95
2009	49	2016	39	2023	85

Table 2, which follows, illustrates the annual scientific production above, showing the number of articles related to this topic over the years. It can be seen that in 2003, there were 32 articles, while in 2023, the number has increased to 85 articles. The data shows an increase in the number of articles related to this topic over time. For more details, please see the chart below.

Based on the observed trends related to this topic, it can be concluded that the role of Artificial Intelligence in the textile industry is increasing annually. The peak of research in the context of AI and the textile industry occurred in 2022, when researchers [45], [46], [47] attempted to integrate AI, including machine learning, prediction tools, and Neural networks. Therefore, further development is needed with a focus on different types and specific aspects related to the application of Artificial Intelligence in the textile industry.

More detailed findings were obtained through VosViewer analysis, which utilized the entire keyword database, revealing the implementation of AI in the textile industry and resulting in four distinct discussion groups. The first co-occurrence (blue) illustrates the application of AI in the textile industry, primarily optimizing supply chains and producing basic textiles. This section explores various aspects of AI, including predictive analytics, Artificial neural networks, decision-making, and computer vision. Furthermore, the second co-occurrence (green) highlights the importance of utilizing AI in waste management within the textile industry. Some emerging applications of AI algorithms, such as those in *membrane technology* and waste *removal efficiencies*, contribute to efficient waste management and recovery.

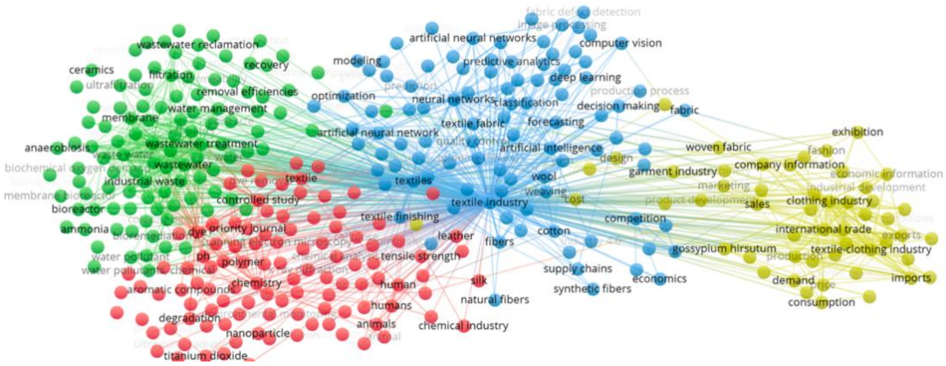

Figure 2. Research Theme: Keyword Analysis

The third co-occurrence, as mentioned in figure 2, focuses on the development of chemical materials and polymers. Some forms of AI used, based on keywords such as *nanoparticles*, *polymer chemistry*, and *degradation*, include *machine learning* and *computational chemistry technologies*. These various AIs simulate various vital chemicals in textiles with the best formulations and perform chemical reaction calculations quickly and accurately. Finally, the third co-occurrence (yellow) shows the use of AI focused on increasing the economic value that includes (export-import) in the fashion industry specifically. Natural language processing (NLP) can be used at this stage to analyze product reviews, demand forecasting algorithms to estimate market needs, and recommendation systems that provide recommendations for relevant textile products.

Based on the analysis of trend and keyword intensity, the following results were found, as shown in table 4 below:

Table 3. Top 10 Author Keyword Occurrences

Words	Occurrences	freq	year_q1	year_med	year_q3
artificial neural network	42	48	2014	2017	2021
artificial neural networks	34	34	2013	2018	2020
textile wastewater	32	32	2015	2020	2022
textile industry	28	28	2015	2018	2021
artificial intelligence	27	27	2018	2021	2022
image processing	16	16	2014	2015	2022
textile effluent	16	16	2015	2019	2021
machine learning	15	15	2019	2021	2022
photocatalysis	14	14	2010	2016	2020
response surface methodology	14	14	2017	2020	2022

After the redrafting process, it was seen that the three main author keywords were "ANN" (Artificial Neural Networks), "image processing," and "machine learning." This indicates that these three topics are getting significant attention, as reflected in the number of occurrences of the top author keywords. This shows that these topics remain highly relevant and warrant further development in future research.

The movement of the research topic is evident through a thematic map diagram that features two dimensions, based on the values of centrality (x-axis) and density (y-axis). The image contains four quadrants, namely the motor theme, an essential theme with high centrality; in this quadrant, keywords regarding smart textiles, especially fiber and ANN, are the most discussed. This means that researchers currently see the urgency of using AI in the textile industry, which is more focused on making basic materials and using ANN. Furthermore, the quadrant of basic and transverse themes is a theme that has a strong centrality but low development. Common basic themes, such as decolorization, textile and apparel, cotton, and photocatalyst, have been widely discussed and have a very high level of intensity.

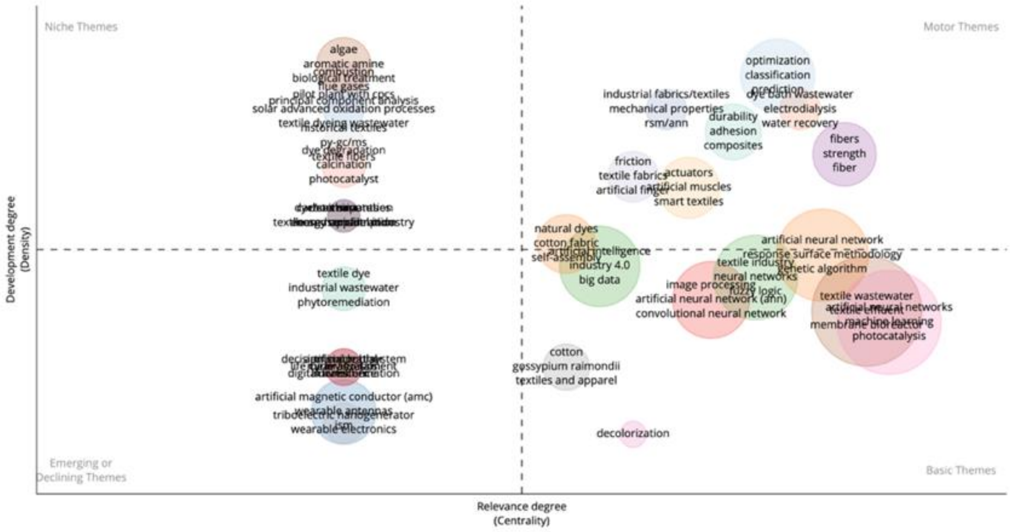

Figure 3. Thematic Map

In addition figure 3 describes the emerging or declining Theme quadrant represents themes that require qualitative analysis to understand whether these themes have emerged or lost their relevance, such as Artificial Magnetic Conductor (AMC) and Wearable electronics have begun to be primarily abandoned considering that these keywords are the earliest in AI research and have grown more complex today, including in the textile industry. The last quadrant is a niche theme, a highly developed theme or cluster with a more significant gap. Specific themes, such as using renewable materials in textiles like algae and aromatic amines, allow for more in-depth exploration by researchers in the sector. The extracted contribution of AI in the textile industry is shown in table 4.

Based on the results of the analysis in table 4, the use of AI has significantly contributed to textile industry players creating quality and efficient products simultaneously. Overall, machine learning (ML) and Neural Networks (ANNs) are the most widely used types of AI. AI is used to create predictions and analyses of ingredients and chemical content, as well as to detect product damage. Even the research [50] showing an accuracy of up to 97.85% signifies that AI can play a crucial role in improving the efficiency and effectiveness of quality control processes in the textile industry, potentially reducing costs and improving customer satisfaction. Thus, empirical testing and AI development in this context must continuously be carried out to create an ideal and sustainable production process.

Table 4. The contribution of AI in the textile industry

Manufacturing Aspects	Types of AI	Success	Subject Industry	Source
Production & Supply Chain Optimization	ML, Evolutionary Multi-objective Optimization (EMO), Robotics	Reduce waste, time, and production costs.	All Fabrics: Including Yarn(s), Fabric(s), Sliver textile, Fiber, Wood, Leaf (including raw material textile)	[20], [38], [39], [40], [41]

Fabric Defect	ANN, DCNN, CNN Machine/Computer Vision	Up to 97.85% accuracy in fabric defect detection, reducing manual inspection.	All Fabrics	[20], [38], [39], [40], [42], [43]
Wearable Technology	DL, Neural Networks, Remote Monitoring	Accurate biometric monitoring, supporting medical applications and fabric requirements on specific activities (e.g., sports).	Smartpant, Textile headband	[44], [45]
Computational Chemistry Tech	CNN, ANN	Improve the accuracy of material property prediction with low error (<5%).	Yarn(s), Fabric(s), Braided-textile reinforced, Fiber	[46], [47]
Yarn Spinning Process	ANN, Genetic Algorithm (GA)	High prediction accuracy reduces uncertainty in yarn spinning.	Yarn(s), Sliver textile	[40], [41], [48], [49], [50], [51]
Construction Textile Analysis	Multilayer Perceptron (MLP), ANN, SVM	Enhance the prediction of bending load capacity for construction materials with more accurate results.	Textile reinforced, Textile reinforced mortal, Braided-textile reinforced	[39], [42], [50], [52], [53], [54], [55]
Textile Waste Management	ML, ANN, Membrane Technology, Remote Sensing	Enhance waste management efficiency and support informed decisions for sustainability.	Solid Waste (including textile), Textile industrial wastewater, Plastic	[20], [42], [48], [56], [57]
Sustainability	ML, ANN	Reduction of energy consumption by up to 15%, reduction in the use of hazardous chemicals, and optimization of natural resources.	Organic Compound (include Textile), Leaf (include raw material textile)	[41], [48], [56], [57]

Given the critical role of AI integration in the textile industry, understanding the key sectors and disciplines that drive its successful implementation is essential. The insights gained from this analysis will form a valuable foundation for developing a targeted research agenda that addresses the industry's most pressing needs and opportunities, as follows:

3.1. Motor-theme growth topics

3.1.1. Machine Learning and Data Analytics

Various studies have shown that machine learning contributes significantly to every integration of AI in the textile industry; thus, disciplines that focus on this aspect are urgently needed. *Machine learning* and data *analytics* are essential in managing large-scale data to provide recommendations for correct and reliable decisions. In particular, the textile industry, sensitive to market demand [58], [59] and changes in consumer behavior, supply chain availability, and vulnerability [59], requires optimal analytics. With the right algorithms, companies can optimize their supply chains, reduce waste, and ultimately increase efficiency and profitability.

3.1.2. Fabric Defect Detector

The discipline of deep learning is more closely tied to convolutional neural networks (CNNs), deep convolutional neural networks (DCNNs), and computer vision, which offer numerous benefits to industry players through more in-depth and complex product analysis [59]. In the textile industry, these various AI detector approaches can be optimized to detect fabric defects with unique patterns, which are difficult to detect through manual human checks [60], [61]. By leveraging models trained on extensive imagery data, companies can enhance quality control and expedite inspections.

3.1.3. Robotics and Automation

Robotics and automation technologies play a crucial role in production efficiency. The use of robots is employed to perform repetitive tasks, such as sewing, cutting, and packaging, more accurately, thereby reducing defects in the initial stage of product distribution [62]. By adopting automation, the textile industry not only reduces labor costs but also improves the consistency and quality of the final product, as well as speeds up production time.

3.1.4. Adaptive Neuro-Fuzzy Inference Systems (ANFIS)

ANFIS can combine the principles of fuzzy logic and neural networks to handle uncertainty and complexity in data [63]. In this context, not only computing skills but also an in-depth analysis of neural composition are required. In the textile industry, ANFIS can enhance demand prediction and quality control by considering variables that are challenging to measure or predict within the user's context, thereby facilitating better decision-making, especially in situations involving high uncertainty.

3.1.5. Geospatial Analysis and Sensor Technology

Geospatial analysis and sensor technology allow real-time monitoring and analysis of product and process conditions. In the textile industry, this can be used to monitor waste distribution and identify areas that require improvement. Sensor technology can also collect data from production machines and environments, which are then analyzed to improve efficiency and sustainability.

In addition, the results of the analysis, extracted from the article summaries, will identify research gaps and inform future research agendas based on bibliometric analyses processed with RStudio Biblioshiny. These results will be divided into several sections related to the research agenda and the various gaps identified.

3.2. Discussion Research Agenda 1: Empirical Analysis

From the examination, it can be seen that none of the articles incorporate research objectives that include quality improvement, proposed models, and model optimization. The main research gaps identified are those that seek proposed models that are optimal for quality improvement in the textile industry. Further research can be conducted using empirical analysis using quadratic regression, *Support Vector Machine (SVM), ANN, and CNN.* This effort will help determine the extent of the effectiveness of AI use in the textile industry for more specific product types, as shown in table 5 below.

Table 5. Research Agenda: Empirical Analysis

Relevant Further Research	Cluster (Manufacturing Aspect)	Identified Research Gap	Recommended Statistical / ML Techniques	Source
Enables robust AI-based inspection for textile manufacturing; supports digital transformation in quality control.	Fabric Defect	Lack of automated, accurate image-based detection for multiple textile defects; prior ML approaches limited in efficiency/generality.	Multi-class SVM (RBF, polynomial), cross-validation, versus ANN.	[39]
Advances smart/textile manufacturing productivity and predictive automation; technological roadmapping.	Production & Supply Chain Optimization	Insufficient robustness/scalability of AI monitoring systems in real heterogeneous industrial datasets; lack of cost-effective, precise ML modeling for yarn tensile properties; prior works limited in generalization and agility from lab to factory.	Deep learning models (CNN, GAN, GNN, LSTM), transfer learning, hybrid ML; Feed-forward ANN (Levenberg-Marquardt), image processing, error metrics.	[20], [52]

Drives automated, AI-enhanced textile testing/quality control; supports industry adoption.	Textile Waste Management	Few studies use wheat straw activated carbon (WSAC) for real effluent and lack full multi-variable AI optimization (ANN-GA/RSM-GA with new microalgae) on textile effluent; past works focus only on narrow process variables.	Response surface methodology, ANN, kinetic/reactor models, ANOVA; Hybrid ANN-GA/RSM-GA, error analysis, multi-variable optimization.	[64], [65]
Targets sustainable, ML-optimized wastewater treatment; aligns with circular economy for textiles.	Computational Chemistry Tech	Reliance on expert and empirical fiber length prediction; scarce real-world ML for high-dimensional cellulose refining control.	Feed-forward ANN, PCA feature selection, hierarchical clustering, ANOVA.	[66]
Supports eco-friendly, AI-driven bioremediation in textile/carpet industry; relevant for compliance/sustainability.	Construction Textile Analysis	Limited predictive ML models/composite design for braided-textile tubes; weak experimental diversity in prior work.	Multi-layer ANN, Levenberg-Marquardt, error metrics, feature importance.	[55]

3.3. *Research Agenda 2: Focus of Research Subjects*

Subjects extracted from the study can be categorized into three main domains: yarn, fabric, and other subjects. In contrast, different articles are related to non-textile subjects. These findings highlight potential future research trends, especially in fabric-related research domains. In addition, further research can also develop its subjects in the health sector, logistics, and supply chain analysis with the effective use of AI. Table 6 describes research focusing on customization and quality management for all types of fabrics, which is also necessary to cater to users' more complex textile needs.

Table 6. Research Agenda: Focus of Research Subject

Relevant Further Research	Cluster (Manufacturing Aspect)	Identified Research Gap	Recommended Statistical / ML Techniques	Source
Focus on thread optimization and leveling actions, as well as customization analysis in the context of quality and supply chain optimization	Yarn Spinning Process, Production & Supply Chain Optimization	Manual LAP determination is time-consuming, leads to material and cost losses; conventional methods are inefficient for auto-leveling draw frames across variable materials/settings.	Feed-forward ANN (Levenberg-Marquardt), Bayesian regularization, normalization, 10-fold cross-validation, error metrics (MAE, R^2).	[67]
Focus on the gas plasma effect to see the surface properties of the fabric and how this can be applied in the production process	Construction Textile Analysis	Insufficient systematic modeling of plasma surface modification outcomes on textiles; complexity in parameter influence, lack of multi-feature analysis and effective data-driven prediction.	Feed-forward ANN (Levenberg-Marquardt, Bayesian regularization), fuzzy logic feature selection, statistical error metrics (RMSE, R, MAE, MRAE), connection weights for input importance.	[68]

Medical applications of smart textiles and how this technology can be integrated with existing health monitoring systems	Wearable Technology	No effective multimodal inactivity recognition for wearable/resource-constrained textile health systems; lack of unobtrusive, high-accuracy multi-class in-bed posture detection; conventional regression inadequate for universal/non-ambulant height and weight estimation.	Feature fusion (accelerometer, heart rate), ML classifiers (SVM, KNN, ANN, etc.), cross-validation, Feed-forward ANN (HoG, LBP, PCA), ML regressions (SVR, GPR), error/RMSE.	[69], [70], [71]
Application of SC-CO2 in textiles will help predict solubility, and similarly, modeling other physical properties of interest	Computational Chemistry Tech	Prior QSPR/ML solubility models limited to chemically similar compounds or non-public software; lacked generalizability to diverse organics, especially for textile/industrial use.	ANN-based QSPR with open-source tools, 42 molecular/thermodynamic descriptors, backpropagation, MSE/R^2 evaluation, training-validation-test set.	[72]
Application of Polymer Optical Fiber (POF) *smart pants* for remote monitoring of textile product users	Wearable Technology	Few textile-integrated sensor systems enable reliable, real-time biomechanical monitoring and activity recognition outside lab settings; prior smart garments limited by cost, privacy, or wearability.	Feed-forward ANN, PCA for feature selection and sensor reduction, time-frequency analysis, accuracy (cross-validation).	[44]

3.4. Research Agenda 3: Approaches and Methods

The dominant AI method approach used for AI implementation in the textile industry is artificial neural networks (ANNs) with 25 articles, followed by Machine Learning/Deep Learning with 21 articles, computer/machine vision with eight articles, CNN with five articles, fuzzy logic with three articles, and additional methodological approaches that complement various other methodologies. This analysis reveals a research gap that needs to be addressed, specifically the need for a combination of various methodological approaches in AI to achieve faster and more accurate results. In addition, the YOLO method has yet to be applied to fabric pattern recognition, a future research area with significant potential for solution development, as shown in table 7 below.

Table 7. Research Agenda: Approach & Methods

Relevant Further Research	Cluster Manufacturing Aspect	Identified Research Gap	Recommended Statistical / ML Techniques	Source
Exploring a combination of various AI methodologies, including fuzzy processes and ANNs, to improve long-term prediction accuracy	Textile Waste Management, Construction Textile Analysis	Lack of robust, multi-variable modeling for long-term prediction and uncertainty in textiles; insufficient hybrid approaches integrating fuzzy logic and advanced neural nets	ANFIS hybridized with PSO/GA, interval/fuzzy RNN, clustering, cross-validation, RMSE	[48], [50]
Integration of ensemble techniques that combine logistic regression and ANN to get better performance in predicting financial stress	Production & Supply Chain Optimization	Prior approaches used either statistical (LR) or single ML, limiting performance/generalization for financial distress in textile supply chains	Ensemble learning: LR+SVM+BPNN, stepwise regression, cross-validation, multi-error measure	[38]

Exploration of different ANN model parameters to improve the accuracy of tenacity and unevenness prediction in yarns	Yarn Spinning Process, Fabric Defect	Classic models lacked simultaneous robustness for multi-property yarn prediction and parameter tuning for higher accuracy	Multi-layer BPNN, ANFIS (hybrid fuzzy-ANN), GA optimization, multiple statistical indices	[49], [51], [73]
The use of the YOLO method for fabric pattern recognition for the development of innovative solutions in the textile industry	Computational Chemistry Tech, Fabric Defect	Limited advanced object detection/XAI for textile pattern/stage-based classification and explainable AI for deployment	YOLOv5, Vision Transformer, U2-Net, Grad-CAM, deep learning transfer, precision-recall-F1, multiclass datasets	[42], [74]
Accurately predict coloration by combining various methodologies such as machine learning, SVM & ANN	Textile Waste Management, Fabric Defect, Construction Textile Analysis	Sparse data on real textile effluent and coloration, little benchmarking; need multi-method ML for coloration/dye removal and grading	Polynomial regression, SVM, ANN, image processing, wavelet filters, multi-metric fit, batch/kinetic modeling	[53], [65], [75]
Development of more comprehensive datasets, such as deep learning and learning Vector Quantization (LVQ) Networks, and various other approaches for defect detection and quality control	Fabric Defect, Production & Supply Chain Optimization, Quality Inspection, Maintenance	Industry needs fast, robust, generalizable, multi-class defect QA; prior work lacked large, public data and lightweight, scalable deep models	Deep CNN, AlexNet, MobileNetV2 (transfer learning), BPN/LVQ/MLP, edge computing, hybrid neuro-symbolic, GLCM/GLRLM features, cross-validation, benchmarking	[20], [40], [42], [43], [53], [76], [77], [78]

3.5. *Research Agenda 4: Sustainability and Environmental Impact*

AI has brought the textile industry to a more profound awareness of sustainability and energy efficiency. Further research can focus on this area, emphasizing the importance of using AI and related technologies to promote sustainability and reduce environmental impact in the textile industry. With a focus on waste management, research can explore new models that utilize machine learning to enhance resource utilization efficiency and minimize waste. In addition, applying technologies such as forward osmosis and using hybrid models in waste treatment can open up new opportunities for environmentally friendly practices, helping the textile industry adapt to the growing demands of sustainability. Table 8 will help to extract and describe sustainability and environmental impact as part of research agenda 4.

Table 8. Research Agenda: Sustainability and Environmental Impact

Relevant Further Research	Cluster Manufacturing Aspect	Identified Research Gap	Recommended Statistical / ML Techniques	Source
Use of the ANFIS model to identify more sustainable waste management in the textile industry	Textile Waste Management, Sustainability	Lack of robust, AI-driven modeling of seasonal variation effects on physical composition of municipal/textile waste; prior studies relied on manual/empirical estimation; insufficient multi-variable, data-driven prediction	Adaptive Neuro-Fuzzy Inference System (ANFIS) hybridized with Particle Swarm Optimization (PSO) and Genetic Algorithm (GA), multiple clustering, RMSE, MAD, rMBE	[48]
Optimizing the use of hybrid techniques in textile waste	Textile Waste Management, Sustainability	Sparse work on real textile effluent, few studies using wheat straw AC, little focus on	Central Composite Design, Polynomial Regression, Feed-forward ANN (Levenberg–Marquardt),	[56], [64], [65]

management can be a focus to improve industrial sustainability		mechanistic/process/model optimization with ML	Kinetic Modeling, Multi-metric fit (R^2, MSE, RMSE), batch reactor	
Development of sensor technology applications to monitor and reduce the environmental impact of textile production	Smart Textiles, Wearable Sensing & Personalized Gait Analysis	Conventional smart insoles/machine vision for gait analysis suffer poor comfort, bias, costly labeling, low robustness, generalization issues	All-textile pressure sensor array (embroidered electrodes), LeNet CNN, SVM, Random Forest, MLP (BP) baseline comparison, cross-validation, confusion matrix, ablation study, real-time analytics	[79]
Forward osmosis can be expanded to explore applications in other processes in more environmentally friendly industries	Generic/Universal AI in Manufacturing/Process Optimization	Classic kNN sensitive to hyperparameters; lacks robustness for industrial/large-scale data, high computational cost	kNN-GNN (graph neural network), message passing, end-to-end kNN, deep learning, embedding, Adam optimizer, comparative validation	[56]
The use of AI techniques in reducing plastic pollution in the aquatic environment related to the textile industry	Environmental Quality Monitoring, Remote Sensing for Waste	Manual net/trawl surveys and inspection are costly, slow, non-standardized; prior automation lacked high-resolution, robust, multiclass plastic detection (floating/shoreline)	Dual CNN pipeline (PLD-CNN for detection, PLQ-CNN for classification/quantification), SVM/RF baselines, drone imaging, data augmentation, cross-validation, real-world benchmarking	[48], [57]

4. Conclusion

This study contributes a statistically grounded framework for mapping the evolution of AI-related research in the textile industry. By integrating bibliometric network analysis with systematic scoping review, we offer more than a descriptive landscape: we reveal the underlying statistical structures, keyword co-occurrence patterns, cluster topologies, and citation trajectories, that shape the knowledge domain. Unlike prior reviews that primarily catalog technologies, this approach applies association strength normalization, VOS modularity clustering, and frequency-weighted thematic analysis to derive empirical signals from textual and citation data. These signals directly informed the formulation of research agendas, aligning emerging AI methods with measurable production and sustainability outcomes in textile manufacturing.

The novelty of this work lies in linking statistical evidence from bibliometric clusters to targeted AI research pathways. For example, the statistical dominance of ANN and SVM in high-centrality clusters underpins Agenda 1, which emphasizes rigorous model validation, error distribution analysis, and regression–classification hybridization. Similarly, statistical convergence between waste management and sustainability clusters provides a data-driven rationale for advancing Agenda 4 through sensor fusion models and hybrid empirical testing. This analytic design demonstrates that statistical reasoning is not limited to model development but can also govern how research gaps are surfaced and structured.

More broadly, this study establishes a statistical roadmap for transforming bibliometric signals into evidence-based research design. By reframing bibliometric analysis as a statistical instrument rather than a purely descriptive tool, the paper opens space for future empirical studies to embed hypothesis testing, regression modeling, and predictive analytics at the core of textile innovation. This statistical orientation strengthens both the methodological rigor and the strategic foresight of AI implementation in manufacturing, positioning future research at the intersection of data science, engineering, and applied statistics.

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