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ARTIFICIAL INTELLIGENCE FOR SUSTAINABLE TEXTILES: A REVIEW OF CIRCULAR ECONOMY APPLICATIONS

ELIAS RANDJBARAN[1*], DARYA KHAKSARI[2], HAMID MEHRABI[3], RIZAL ZAHARI[4], DAYANG L. MAJID [1], MOHAMED T. H. SULTAN[1], NORKHAIRUNNISA MAZLAN[1], MEHDI GRANHEMAT[5]

[1]Department of Aerospace Engineering, Faculty of Engineering, Universiti Putra Malaysia, Serdang, Selangor, 43400 UPM, Malaysia
[2]Department of Advanced Manufacturing, Aircraft Composite Inc. 12 Jalan Jemuju Dua 16/13b, Seksyen 16, 40200, Shah Alam, Selangor, Malaysia
[3]Faculty of Technology, School of Engineering, University of Sunderland, Sunderland SR1 3SD, UK
[4]Department of Aeronautical Engineering Technology (HCT), Faculty of Engineering Technology and Science, Higher Colleges of Technology, Al-Ain, Abu Dhabi P.O. Box 25026, United Arab Emirates
[5]Lincoln University, Wisma Lincoln, No. 12-18, Jalan SS 6/12, 47301 Petaling Jaya, Selangor Darul Ehsan, Malaysia

ELIAS RANDJBARAN: Elias@gmx.co.uk

Corresponding Author: ELIAS RANDJBARAN

Abstract
The integration of Artificial Intelligence (AI) and Machine Learning (ML) presents a paradigm shift for enhancing sustainability within the textile industry. This review examines the transformative potential of these technologies in fostering a circular economy, with a focus on material design, process optimisation, and end-of-life solutions. It surveys applications across textile science, from natural fibre composites to technical and smart textiles, highlighting the role of predictive modelling and ML algorithms—including neural networks, convolutional neural networks (CNNs), and random forests. These techniques are demonstrated to enhance the design of fibre-based materials, predict key properties such as tensile strength and thermal stability, and optimise manufacturing processes like dyeing and weaving. Furthermore, the review explores the significant contribution of computer vision to automated quality control, defect detection, and the assessment of garment condition for resale, thereby supporting circular business models. A central theme is the capacity of AI to drive sustainability by enabling zero-waste pattern design, improving colour prediction accuracy to reduce chemical waste, and advancing automated textile sorting for recycling. Despite this promising progress, the principal challenges identified are not algorithmic but systemic, relating to data scarcity, integration complexities, and the need for cross-sector collaboration. The review concludes by identifying critical future research directions, emphasising the need for robust, physics-informed models, the collaborative development of larger, more diverse datasets, and AI-driven Design for Disassembly (DfD) to fully realise AI's potential in creating a more innovative, efficient, and sustainable textile industry.

Keywords: Artificial Intelligence; Circular Economy; Textile Recycling; Predictive Modelling; Computer Vision; Sustainable Manufacturing

1. INTRODUCTION

Positioning sustainability at the core of its development, the global textile industry—valued at approximately \$1.97 trillion in 2024 and projected to reach \$4.01 trillion by 2034—faces the urgent challenge of reconciling formidable growth with pressing environmental imperatives [1]. This expansion, driven by rising demand for fast and customised products, is underpinned by a predominantly linear model of consumption, which generates an estimated 92 million tonnes of waste annually [2]. This waste stream, largely managed through incineration, landfilling, or export, represents a profound environmental burden and a significant economic loss, estimated at USD 500 billion each year due to underutilised garments and inadequate recycling [3]. The scale of the challenge is further highlighted by the stark disparity in 2024 between the 12% of discarded textiles that are reused and the less than 1% of material from used clothing that is recycled into new fibres [4]. It is within this context of systemic inefficiency

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and environmental impact that artificial intelligence (AI) emerges as a potentially transformative force, offering novel pathways to redefine production and consumption paradigms and advance the principles of a circular economy [5].

Figure 1 summarises how artificial intelligence and machine learning underpin a transition to circularity in the textile sector. At the apex, a boxed node lists principal AI methodologies such as neural networks, convolutional neural networks, random forests and computer vision. Arrows descend to three primary application domains: predictive material and product design, manufacturing process optimisation and automated quality control. Each domain is annotated with representative activities — for example, natural-fibre composites and smart fabrics under design; dyeing, spinning and weaving under process optimisation; and defect detection and garment condition assessment under quality control. These applications converge on a central circular-economy node, illustrated with the recycling motif, which connects to specific closed-loop outcomes including zero-waste pattern cutting, colour-accurate dyeing to reduce rework, textile sorting for recycling and closed-loop recycling. The visual hierarchy emphasises a flow from data-driven methods to tangible sustainability outcomes, while also implying feedback loops for continuous improvement. The diagram is well suited for a review article, clarifying how AI interventions can reduce waste and extend product life within an integrated circular framework.

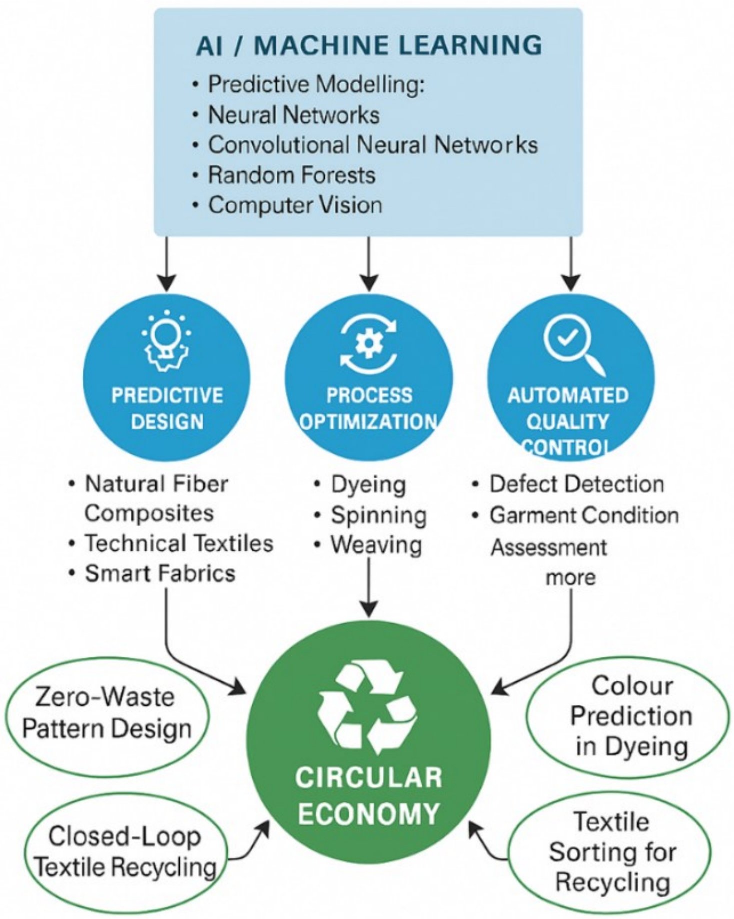

Fig. 1 Transforming Textile Sustainability through Artificial Intelligence: schematic linking AI/ML techniques to design, process optimisation, automated quality control and circular-economy outcomes.

The concept of a circular economy in textiles aims to minimise waste through reuse, repair, refurbishment, and recycling of materials and products, creating closed-loop systems that extend product lifecycles and reduce environmental impact [6]. However, transitioning to such a model presents complex challenges, including efficient sorting of textile waste, accurate assessment of garment condition, and optimisation of manufacturing processes to reduce waste. AI technologies, particularly machine learning, deep learning, and computer vision, offer promising solutions to these challenges by enabling automated, data-driven decision-making offering speed, accuracy, and scalability across the textile value chain [7].

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This review paper examines the integration of AI and ML technologies in the textile industry through a circular economy perspective, focusing on their potential to enhance sustainability across multiple domains. The analysis spans AI applications in material design and development, manufacturing process optimisation, quality control, textile property prediction, and end-of-life management. Special attention is given to the role of AI in advancing smart textiles and technical textiles containing flexible electronics, while addressing the sustainability challenges associated with these innovative materials. Additionally, the paper explores how predictive modelling and computer vision can facilitate textile recycling and reuse, thereby supporting the transition to a circular economy.

Despite these promising applications, the widespread implementation of AI in the textile industry faces significant challenges. These include data scarcity, issues of model interpretability and transparency, computational demands, and difficulties in model generalisation [7,8]. This review provides a critical examination of these limitations and identifies pivotal future research directions required to harness AI's full potential. By synthesising recent advances and highlighting innovative applications, this paper offers a comprehensive overview of the role of AI in transforming textile sustainability through a circular economy lens.

The paper is structured as follows: Section 3 (Results) presents the systematic review findings, organised across three primary domains—AI in Textile Design and Materials Development, AI in Sustainable Manufacturing and Process Optimisation, and AI for Circular Economy and End-of-Life Solutions. Section 4 (Discussion) provides a critical analysis of the prevailing challenges and limitations before delineating specific future research pathways. The review concludes with Section 5, which summarises the transformative potential of AI for the sector.

2 METHODS

This systematic review followed the PRISMA guidelines (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) to ensure a comprehensive and transparent methodology for identifying, selecting, and critically evaluating relevant research on AI applications in textile sustainability. The review process encompassed clear objectives, specific eligibility criteria, systematic search strategies, and a structured data extraction process to minimise bias and ensure methodological rigor [9].

2.1 SEARCH STRATEGY AND INFORMATION SOURCES

A comprehensive literature search was conducted to identify relevant peer-reviewed journal articles, conference proceedings, and technical reports published between 2016 and 2024. This eight-year timeframe was selected to capture the most significant and recent advancements in the rapidly evolving field of artificial intelligence. The search was executed across several major academic databases, including ScienceDirect, IEEE Xplore, Springer Link, Taylor & Francis Online, and SAGE Journals, with Google Scholar utilised for supplementary discovery.

The search strategy employed a structured combination of keywords and Boolean operators, built around three core conceptual domains:

i. Artificial Intelligence Techniques: encompassing terms such as "artificial intelligence," "machine learning," "deep learning," and "computer vision."
ii. Textile and Fashion Context: including "textile," "fabric," "fashion," and "garment."
iii. Sustainability and Circular Economy: focusing on "circular economy," "sustainability," "recycling," "waste management," and "sustainable manufacturing."

2.2 ELIGIBILITY CRITERIA AND STUDY SELECTION

The study selection process employed explicit eligibility criteria to ensure the review's relevance and rigour. The inclusion criteria required that studies:

- Primarily investigated AI/ML applications within the textile value chain, encompassing design, manufacturing, quality control, sorting, or recycling.

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- Presented empirical findings or detailed technical implementations, excluding purely conceptual frameworks.
- Explicitly addressed environmental sustainability objectives, such as waste reduction, resource efficiency, or circular economy principles.

Were published in English between 2016 and 2024 and were available in full text.

Conversely, studies were excluded based on the following criteria:

- A sole focus on consumer-facing applications (e.g., e-commerce recommendation systems) without direct environmental sustainability implications.
- Insufficient technical detail or methodological description to evaluate the AI application.
- Duplicate publications or non-peer-reviewed articles, with the exception of technical reports from established research institutions.

The initial search identified 135 potentially relevant research resources. After removing duplicates and applying eligibility criteria through abstract and title screening, 86 records underwent full-text assessment. Ultimately, 49 studies met all inclusion criteria and formed the core evidence base for this systematic review. The selection process was conducted independently by two researchers, with disagreements resolved through discussion or consultation with a third researcher when necessary.

2.3 DATA EXTRACTION AND ANALYSIS

A standardised data extraction form was developed to systematically capture key information from each included study. Extracted data included: (1) bibliographic information; (2) research objectives and methodology; (3) AI/ML techniques and algorithms employed; (4) textile applications and processes addressed; (5) sustainability benefits and outcomes; (6) datasets used and their characteristics; and (7) key findings and limitations. The extracted data were analysed using thematic analysis to identify patterns, applications, and challenges across the studies. Results were synthesised narratively and organised according to key thematic areas aligned with the textile value chain and circular economy strategies.

3 RESULTS

3.1 AI IN TEXTILE DESIGN AND MATERIALS DEVELOPMENT

The integration of Artificial Intelligence into textile design and materials development represents a paradigm shift in how fabrics are conceived, engineered, and optimised for specific applications [10]. AI technologies are enabling unprecedented advancements in predictive modelling of material properties, development of smart textiles, and creation of sustainable material systems that align with circular economy principles [7,10–13]. These innovations span the entire spectrum of textile design, from molecular-level material engineering to functional fabric development [6,11,12].

3.1.1 PREDICTIVE MODELLING FOR MATERIAL PROPERTIES AND SMART TEXTILES

Machine Learning (ML) algorithms have demonstrated considerable efficacy in predicting the properties of polymer textiles and fibre composites, offering a pathway to accelerate materials design and reduce reliance on costly experimental procedures [14–16]. Techniques such as artificial neural networks (ANNs), Gaussian process regression (GPR), and random forests have been successfully employed to forecast key mechanical, thermal, and functional properties from material composition and processing parameters [14,15].

For instance, Le et al. [17] developed a GPR model that accurately predicts the tensile strength of polymer/CNT nanocomposites. The model demonstrated high performance, with testing RMSE and MAE values of 5.327 MPa and 3.539 MPa, respectively, representing a high degree of accuracy given the broad tensile strength range of the dataset (0.55–190 MPa). This was corroborated by excellent correlation metrics, including an R value of 0.993 and an index of agreement (IA) of 0.996 on the test set. The study further established the superiority of GPR over six other ML methods based on RMSE. A notable discrepancy

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was observed in the mean absolute percentage error (MAPE) value of 33.394%, which is mathematically inflated by the wide data range and the presence of values close to zero, and thus does not contradict the strong performance indicated by the other metrics [17]. This capability to model complex property relationships underscores the transformative potential of ML in guiding the development of advanced, sustainable textile materials.

Further demonstrating this potential, Iannacchero et al. [29] employed an ML-driven approach to optimise the design of conductive e-textiles. The study utilised Tencel yarn coated with polypyrrole (PPy), an intrinsically conductive polymer valued for its electrical properties and environmental stability [29–32]. To overcome PPy's inherent brittleness, the researchers applied Bayesian optimization and Pareto front analysis across 11 experimental trials. This process successfully identified ideal reaction conditions that minimised electrical resistance to 0.067 kΩ (22.3 Ω cm^{-1}) while simultaneously enhancing conductivity and cost-efficiency. The resulting optimised yarns were woven into prototype fabrics, confirming their viability for use in flexible wearable systems and heating applications [29]. The environmental robustness of such PPy-based textiles is supported by their demonstrated stability through simulated washing cycles and exposure to artificial sweat [29, 33].

The transition of AI-enabled smart textiles from research to commercial application is now evident. Companies are leveraging AI across the product lifecycle, from material design to data analytics. For example, Myant's SKIIN platform integrates biometric monitoring directly into garments for health and wellness applications [34]. In a collaborative effort, Garmin and Chronolife have integrated AI-powered smart textiles with embedded sensors into washable garments to facilitate remote patient monitoring [35]. Other innovators, such as Sensoria, focus on niche applications like AI-powered sensorised socks for performance monitoring and injury prevention [36]. A critical function of AI in this sector is the analysis of vast biometric datasets to generate health insights, alongside the optimisation of fabric properties for comfort and functionality. The growing market for these intelligent garments across medical, fitness, and occupational sectors highlights a significant shift towards data-driven, functional apparel, with AI serving as a core enabler of this innovation.

3.1.2 SMART TEXTILES AND FUNCTIONAL MATERIALS

The integration of Artificial Intelligence (AI), particularly machine learning (ML) and deep learning (DL), is catalysing the development of next-generation smart textiles. These intelligent, responsive fabrics are finding applications in remote health monitoring, performance sport, and adaptive clothing, functioning as continuous, self-powered platforms that acquire, process, and interpret physiological and environmental data in real time [11–14,22–28]. A significant impediment to their wider adoption, however, is the scarcity of sustainable alternatives to conventional metallic conductors [12,14]. The resource-intensive nature of material testing for these digitally enhanced fabrics (encompassing both smart textiles and e-textiles) presents a further barrier. ML-assisted approaches directly address these challenges by employing techniques such as Bayesian optimization and Artificial Neural Networks (ANNs) to efficiently navigate complex parameter spaces, thereby optimising material compositions and manufacturing settings to enhance performance and cost-effectiveness while drastically reducing experimental iterations [14].

A representative study by Iannacchero et al. [29] demonstrates this methodology, using ML to design conductive e-textiles based on Tencel yarn coated with polypyrrole (PPy). While PPy is prized for its electrical properties and environmental stability [29–32], its inherent brittleness often limits standalone use in flexible applications. To overcome this, the authors utilised Bayesian optimization and Pareto front analysis, which identified optimal reaction conditions within just 11 experimental trials. This process minimised the electrical resistance of the yarn to 0.067 kΩ (22.3 Ω cm^{-1}) while simultaneously improving conductivity and cost-efficiency. The resulting yarns were successfully woven into prototype fabrics, validating their potential for flexible wearable systems and heating applications [29]. The suitability of such PPy-based textiles for durable goods is underscored by their demonstrated chemical stability, including resistance to simulated washing cycles and exposure to artificial sweat [29, 33].

The translation of AI-enabled smart textiles from research to commercial reality is now underway. Beyond optimising material properties, AI is critical for deriving insights from the vast datasets these garments collect. For instance, companies like Myant leverage AI in their SKIIN platform for continuous biometric monitoring in health and wellness garments [34]. Similarly, collaborations such as that between Garmin and Chronolife integrate AI-powered smart textiles with wearable devices to advance remote patient monitoring [35]. Other innovators, including Sensoria, focus on niche applications like AI-powered sensorised

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socks for performance analytics and injury prevention [36]. This evolving market segment, spanning medical, fitness, and occupational wear, highlights a decisive shift towards data-driven, functional apparel where AI is integral to both the product's functionality and its sustainable development.

3.1.3 FABRIC HANDFEEL OPTIMISATION

The subjective perception of fabric 'handfeel' represents a complex optimisation challenge that Artificial Intelligence is uniquely positioned to address. Machine Learning (ML) and Deep Learning (DL) models are now capable of automating the prediction of subjective tactile properties by correlating them with objective data from tactile sensors, visual inputs, and mechanical testing [10, 37, 38]. This capability offers a substantial sustainability advantage; by enabling accurate digital prototyping, it significantly reduces the reliance on physical sample production and the associated consumption of energy and materials inherent in traditional laboratory testing [38, 39].

A systematic review of these AI-driven techniques confirms their high predictive performance, consistently exceeding 80% accuracy in forecasting key handfeel attributes such as softness, stiffness, and drape, even with datasets ranging from dozens to several hundred fabric samples [10]. This performance is evidenced by strong results across both classification and regression tasks. For instance, in classification:

- Models achieved 92% accuracy for texture recognition (roughness/smoothness) [40].
- Deep learning models like ResNet-50 reached up to 99.3% accuracy in classifying woven fabric types [41].

For regression-based prediction of continuous subjective properties, models demonstrated high correlation and low error rates:

- Artificial Neural Networks (ANNs) showed 83.5% prediction accuracy for drapability and tactile softness [42].
- Models predicting fundamental mechanical properties—key inputs for handfeel—achieved accuracies of 90.2% [43].
- An Adaptive Neuro-Fuzzy Inference System (ANFIS) predicting tactile comfort scores yielded an exceptionally low RMSE of 0.0122, significantly outperforming standard deviation benchmarks [44].
- Furthermore, bending stiffness was predicted with error margins consistently below 10% [41]

These AI approaches represent a significant advancement over traditional objective measurement methods like the Kawabata Evaluation System (KES) and Fabric Assurance by Simple Testing (FAST), which rely on physical measurements, they are constrained by being time-consuming, costly, and resource-intensive, and fundamentally struggle to address nonlinear relationships between various fabric properties. In contrast, AI models (like SEDDI Textura) excel in identifying these hidden patterns and offer real-time optimisation, critical for meeting consumer demands and accelerating product development. Furthermore, AI-driven handfeel prediction contributes to sustainability by reducing the need for physical samples and enabling right-first-time production [10,38].

3.1.4 VIRTUAL TRY-ON

Virtual Try-On (VTO) technologies, encompassing 3D design and Augmented Reality (AR), are emerging as critical enablers of sustainability within the textile industry by advancing circular economy objectives [45, 46]. These systems contribute to sustainability across two primary domains. Upstream, VTO facilitates zero-waste design and digital prototyping, drastically reducing the need for physical samples and thereby curtailing raw material consumption, waste, and costs associated with the design cycle [45]. Downstream, by providing accurate visualisations of fit and style, VTO mitigates the environmental burden of high online return rates, directly reducing landfill waste and the carbon emissions from reverse logistics [45, 47–49].

Empirical evidence substantiates these impacts. A study of the Lucky Chouette brand, analysing 11,029 transactions over 2.5 months, demonstrated that VTO implementation led to a 27% reduction in product returns and increased average sales per customer [50]. Complementary research on Taobao, using Partial Least Squares Structural Equation Modeling (PLS-SEM) on 366 consumer responses, confirmed that advanced VTO features can stimulate purchasing while promoting sustainability by reducing irrational stockpiling and subsequent waste [49]. Further validation comes from a mixed-methods study on 4D golf apparel simulation, where 76.9% of participants found the dynamic interface effective for judging fit, highlighting its potential

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to minimise returns due to size uncertainty [48].

Commercial applications reinforce these findings. The AI-powered sizing platform YourFit (by 3DLOOK) enabled a 30% reduction in returns for the brand 1822 Denim, directly curtailing waste from reverse logistics [51]. Similarly, TA3 SWIM reported that 80% of customers purchased the AI-recommended size, with less than 10% of returns attributed to fit issues and a dramatic reduction in 'bracketing' behaviour to under 2% [52]. Collectively, these outcomes underscore the significant role of VTO and AI in enabling data-driven sizing, reducing overproduction, and extending garment lifecycles through improved first-time fit accuracy.

Table 1 summarizes the key achievements, AI techniques, and real-world examples of AI applications across textile design and materials development.

Table 1: AI Applications in Textile Design and Materials Development

Application Area	AI Techniques	Key Achievements	Paper Study Cases / Real-World Example	Ref.
Property Prediction	Gaussian Process Regression (GPR), ANN, Random Forests	Predict tensile strength and aging behavior, achieved RMSE values as low as 5.327 MPa for nanocomposites	A GPR-based model predicts the tensile strength of polymer/CNT nanocomposites. The Random Forest Regressor demonstrated the best performance (R^2 of 0.92) in predicting the natural aging times of glass/epoxy composites.	[17,21]
Smart Textile Development	Bayesian Optimization, Pareto Front Analysis	Identified optimal conditions to minimize electrical resistance to 0.067 kΩ in conductive yarns	Bayesian optimization was used to design fully textile-based conductive e-textile prototypes using Tencel yarn coated with polypyrrole (PPy). Companies like Myant (SKIIN platform), Chronolife, and Sensoria continuously advancing in AI-powered smart textile.	[29,34–36]
Fabric Handfeel Optimization	CNN, Hybrid Models	Predict softness, stiffness, and drape with accuracy exceeding 80%; The AI approach supports "right-first-time" production by reducing the need for physical samples.	92% classification accuracy for texture recognition (roughness / smoothness) and 99.3% accuracy in classifying woven fabric types in studies.	[10]
Virtual Try-On (VTO)	3D virtual design, Augmented Reality (AR), AI-driven mobile body scanning	Enables “zero-waste” design by minimizing physical samples; mitigates the substantial environmental burden of high online return rates.	Some papers reported significant reduction in product return rate (27%), irrational stockpiling and waste; 30% reduction in product returns for 1822 Denim by 3DLOOK's YourFit platfor; 80% of customers purchasing the correct size in TA3 SWIM.	[45–52]

3.2 AI IN SUSTAINABLE TEXTILE MANUFACTURING AND PROCESS OPTIMISATION

The implementation of Artificial Intelligence in textile manufacturing processes has ushered in unprecedented efficiencies, substantial waste reduction, and enhanced sustainability across production stages. From spinning and weaving to dyeing and finishing, AI-driven solutions optimise resource consumption, improve product quality, and minimise environmental impact, key objectives in the transition to a circular economy. These technological advancements enable data-driven decision-making that aligns economic objectives with ecological responsibility.

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3.2.1 PROCESS OPTIMISATION AND PREDICTIVE MAINTENANCE

AI and ML algorithms have demonstrated remarkable effectiveness in optimising complex textile manufacturing parameters and predicting maintenance needs, leading to significant reductions in downtime, often cited between 20–45% [53]. In spinning and weaving processes, AI analyses real-time sensor data on machine vibrations, speed, and tension to make instantaneous adjustments that ensure consistent quality while predicting maintenance requirements [54,55]. This predictive modelling capability was exemplified in research conducted with a Portuguese textile company, where Automated Machine Learning (AutoML) tools were employed to predict yarn breaks during fabric production. The H2O AutoML model achieved an R^2 of 0.73 for predicting weft breaks, enabling proactive measures such as adjusting loom speed, providing special operator attention, or modifying yarn materials to prevent production stoppages [56]. Supporting the tangible benefits of this approach, similar applications of AI-driven predictive maintenance in textile manufacturing have led to quantifiable outcomes, including 40% reduction in unplanned downtime within six months of implementing smart sensor monitoring in a mid-sized manufacturer [57], 19% improvement in overall reliability, leading to a reduction in unplanned downtime in Jaya Shree Textiles (India) [58], 32% reduction in unplanned downtime and an 18% decrease in maintenance costs over a 90-day trial period in a manufacturer that partnered with Mutually Human to adopt Microsoft Fabric platform [59].

The optimisation capabilities extend to dyeing processes, where AI significantly reduces water, energy, and chemical consumption. AI-driven technologies can drastically reduce the amount of water and chemicals required, with capabilities extending to cutting water usage by up to 95% and leading to energy savings of up to 50% [60]. Ant colony optimisation (ACO) algorithms have been successfully applied to predict optimal dye recipes for achieving uniform colour across cotton and bicomponent polyester filament blends. These algorithms minimise colour deviation between reactive dyeing of cotton and disperse dyeing of polyester, ensuring both components achieve the same shade with minimal differences [14,61]. This precise colour matching reduces the need for re-dyeing, as the effective algorithm allows for finding the right combination of reactive dyes without having to make multiple corrections. This capability offers the possibility to remedy wastage during the use of dyes and to reduce the quantity of water used during colour corrections, which traditionally consumes additional resources and generates wastewater [60,61].

3.2.2 AI-ENHANCED QUALITY CONTROL

Computer vision systems powered by advanced AI have revolutionised quality control in textile manufacturing, enabling automated, real-time defect detection with superhuman accuracy. These systems utilise high-resolution cameras and sophisticated AI-based machine vision algorithms [62,63]. Such automated optical inspection systems achieve detection accuracies ranging from over 90% up to 99% [64,65], with specific enhanced models reaching a 97.49% mAP [62], dramatically surpassing the manual human accuracy rate of 60–75% [63,66]. For instance, WiseEye can detect, classify, and grade over 50 common types of defects (or around 40 common fabric defects), including flaws like holes, foreign yarn, slubs (thread errors), dirty marks, dye patches, and oil patches, as well as subtle anomalies such as folds and arc edges, across common types of woven, knitted and nonwoven textile materials with different colors and patterns [64,66,67]. These systems enable inspection across diverse materials and patterns at speeds up to 60 metres/minute, significantly exceeding the human speed of 12–15 metres/minute, while some models can process frames in real-time, achieving high speeds like 102.1 FPS [66,68]. Crucially, these systems incorporate industry-specific optimization, acknowledging that an undetected defect (False Negative - FN) usually has a higher cost to the company, leading to the implementation of FN reduction methods and optimization for key metrics like Precision and Recall [68,69]; resulting performance confirms this focus, with certain enhanced models achieving a Recall of 98.45% and Precision of 91.55% [62], and an improved YOLOv8n model delivering 96.3% Precision and 92.8% Recall [67]. This competitive market features major providers offering commercial systems, such as ISRA Vision GmbH with its Smash inline inspection system and Cloud Xperience solution employing AI-supported classification and segmentation [70], and partnerships demonstrating real-world deployment, like the textile manufacturer utilizing an Advantech Automated Optical Inspection (AOI) system to achieve 99% detection accuracy using the WISE-PaaS Cloud Platform [65].

The integration of AI with machine vision enables adaptive learning, allowing self-learning AI systems to improve inspection accuracy over time by recognising new defect and adapting to varying production conditions, ensuring long-term reliability [71–

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73]. This capability has demonstrated measurable impact in industrial applications, with implementations like Robro Systems' Kiara Web Inspection System (KWIS) achieving exceptional accuracy, such as detecting up to 99.2% of all defects [73,74]. While some machine vision systems generally report an improvement in defect detection accuracy by up to 30% compared to manual inspection methods [75], KWIS deployments have shown even stronger industrial results, including a 40% reduction in rejection rates and a 15% increase in production speed [74]. Such advancements directly contribute to sustainability by identifying defects early in the production process, reducing material waste (with AI-driven systems capable of reducing fabric waste by approximately 20% in large-scale facilities [71]) and preventing resource-intensive rework operations [72,73,75].

3.2.3 SUSTAINABLE PRODUCTION PLANNING

AI-driven predictive analytics, leveraging Machine Learning algorithms such as Long Short-Term Memory (LSTM) and Reinforcement Learning (RL), enable more sustainable production planning through demand forecasting and resource optimization [76,77]. Natural Language Processing (NLP) algorithms analyse customer reviews, social media trends, and market reports to assess consumer attitudes regarding particular styles, colours, materials, and brands in real time [78]. Predicting demand patterns this way helps manufacturers avoid overproduction and inventory waste, leading to a reduction in forecasting errors by up to 25% [77]. This data-driven approach to production planning aligns with circular economy principles by ensuring that production volumes more closely match consumption needs, reducing the volume of unsold goods that typically end up as waste [5]. Several brands utilize these AI techniques. Zara employs AI-powered social listening and Consumer Sentiment Analysis (analysing text, images, and videos) to detect emerging trends, enabling them to issue production orders in precise batches, which has contributed to 85% of items selling at full price (versus a 60% industry average) and has reduced unsold finished goods by nearly 20 percent across pilot categories [79,80]. Similarly, subscription service Stitch Fix relies on Natural Language Processing (NLP) to analyse more than 4.5 billion text data points shared by customers, resulting in 70% of re-buys being driven by AI recommendations, lifting engagement and conversions by 5% to 12% respectively, and achieving a 9–10% growth in average order value [80–82]. Furthermore, a collaboration with Tommy Hilfiger leveraged NLP and social media listening to analyse consumer sentiments and trends, helping the brand rapidly respond to emerging trends and reduce the time-to-market for new collections [82,83], while The North Face uses NLP in its online shopping assistant to understand customer needs, successfully contributing to increased online sales and fewer returns [83].

Furthermore, AI systems facilitate energy efficiency in textile manufacturing facilities through IoT-based sensors and AI-driven monitoring that optimise energy consumption across production processes. These systems, often utilizing models like Adaptive Deep Reinforcement Learning (ADRL-BO), identify energy-intensive operations and suggest operational adjustments to reduce power consumption without compromising output quality [84]. The cumulative effect of these AI applications, from predictive maintenance to quality control and production planning, contributes to a significant reduction in the environmental footprint of textile manufacturing [85]. This technological integration not only achieves measurable resource savings (such as an average of 35% energy savings and 45% maintenance cost reduction) but also strengthens the economic competitiveness of manufacturers [84,86].

3.3 AI FOR CIRCULAR ECONOMY AND END-OF-LIFE SOLUTIONS

Artificial Intelligence plays a transformative role in advancing circular economy principles within the textile industry, particularly in extending product lifecycles, optimising recycling processes, and creating new pathways for waste valorisation [5,87]. AI technologies enable innovative approaches to textile waste management, utilizing integrated pipelines built on Industry 4.0 principles, including automated sorting, precise material identification using spectral imaging, condition assessment, and recycling process optimisation via robotics and laser segmentation (e.g., targeted component removal) [7,88,89], which are critical for transitioning from a linear "take-make-dispose" model to a circular system that maximises resource efficiency and establishes digital traceability aligned with global sustainability goals [5,87].

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3.3.1 AUTOMATED TEXTILE SORTING AND WASTE MANAGEMENT

The sorting of textile waste represents a significant bottleneck in advancing circularity, particularly with the growing complexity of material compositions in modern textiles. AI-driven systems, especially those utilising computer vision and deep learning algorithms, have demonstrated remarkable capabilities in automating and enhancing the accuracy of textile sorting operations. Convolutional Neural Networks (CNNs) and hybrid models can classify textiles by type, physical condition, and recyclability, addressing a critical challenge in textile waste management. These systems can identify material composition, colour patterns, and structural properties at speeds and levels unattainable through manual sorting [89,90]. The application of ML in textile waste sorting has achieved impressive results, with classification accuracy of up to 100% for pure fibres, significantly improving the efficiency of recycling operations. However, the sources confirm these peak results were attained under highly controlled, lab-based conditions using samples with assured composition from commercial catalogues. The main limitation for real-world application remains the need for a sufficiently large database with samples of known composition for supervised training, especially since factors prevalent in a 'noisy, real-world recycling facility', such as blended fabrics, coatings, aging effects, and moisture, introduce spectral variability that significantly reduces classification reliability [90]. On the industrial side, the Berlin-based innovator Circular.fashion is a partner in the FashionSort.AI project, developing an innovative digital sorting solution that uses image recognition and AI to efficiently assign discarded textiles for re-use or recycling [91]. This high-precision sorting is essential for maintaining the quality of recycled materials, as contamination from different fibre types can compromise the properties of recycled textiles. Furthermore, AI-powered sorting enables the identification of garments suitable for reuse versus those destined for recycling, maximising the economic value and environmental benefits of textile waste streams [89,90].

3.3.2 CONDITION ASSESSMENT FOR SECOND-LIFE MARKETS

AI technologies have revolutionised the assessment of garment condition, enabling accurate evaluation of wearability and quality for second-hand markets. Computer vision systems can detect subtle signs of aging and damage, such as colour fading, pilling, surface abrasion, and seam damage, which determine whether garments are suitable for resale, repair, or recycling. This automated assessment capability is particularly valuable for charitable organizations and second-hand retailers that traditionally rely on volunteer labour or manual sorting, which is subjective and time-consuming [7].

The integration of AI in condition assessment supports the second-hand clothing market by providing consistent, objective evaluations that enhance consumer trust and enable accurate pricing [7]. This burgeoning ecosystem is demonstrated by key industry players leveraging AI and digital infrastructure: the luxury resale platform Vestiaire Collective utilizes AI in customer-facing applications, having integrated an AI search engine that converts keyword searches into image pattern recognition for more precise results, alongside plans for AI-powered price recommendations [92]. Furthermore, companies like the traceability leader TrusTrace have launched AI-driven upgrades to their platforms and are recognized as Representative Providers for Digital Product Passports (DPPs), helping manage complex traceability data necessary for long-term circularity [93]. By extending the lifespan of garments through facilitated reuse, AI directly contributes to waste reduction and resource conservation. Research indicates that each garment kept in use for longer periods through second-life markets significantly reduces its environmental footprint across metrics including water consumption, carbon emissions, and waste generation [7,94].

3.3.3 RECYCLING PROCESS OPTIMISATION AND DESIGN FOR DISASSEMBLY

AI plays a crucial role in optimising recycling processes for complex textile products, particularly those incorporating smart textiles with integrated electronics. The convergence of textiles and electronics has created sustainability challenges, as these hybrid materials are difficult to disassemble and recycle using conventional methods. AI-assisted approaches address these challenges by leveraging advanced identification systems, enabling efficient automated dismantling, drawing on methodologies developed for comparable complex hybrid products like e-waste, and pioneering novel recycling techniques [95–97].

AI models and robotics can optimise the disassembly and separation of conductive materials from textile substrates, facilitating the recovery of precious metals and specialised polymers [95]. Additionally, generative AI systems use multi-objective optimization frameworks to suggest design modifications that enhance recyclability, such as minimizing textile waste or

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facilitating easier disassembly via modular architectures and detachable systems,an approach known as design for disassembly (DfD) [95,98].

The potential of AI to drive circularity extends to new business models that prioritise service and performance over ownership. AI-enabled platforms and digital infrastructure (like Digital Product Passports) can facilitate clothing rental, repair services, and remanufacturing by accurately assessing condition, predicting remaining lifespan, and identifying optimal maintenance requirements. These innovative approaches, powered by AI, represent a fundamental shift toward dematerialisation and extended product responsibility that aligns with circular economy principles [99].

3.4 AI-ENABLED TEXTILE RECYCLING TECHNOLOGIES

Recent advancements in AI-enabled recycling technologies have demonstrated significant potential for addressing the global textile waste crisis [7]. These technologies leverage computer vision, robotics, and machine learning to automate the dismantling and processing of used garments, transforming them into high-quality recycling feedstock [100,101]. The development of these systems represents a critical innovation for scaling circular economy solutions in the fashion and textile industry.

3.4.1 AUTOMATED GARMENT DISMANTLING SYSTEMS

Fully automated systems for garment identification, sorting, and disassembly have emerged as promising solutions for addressing the labour-intensive nature of textile recycling, where inaccurate manual sorting often leads to material inefficiency and contamination [89]. Researchers at RIT's Golisano Institute for Sustainability (GIS) have developed an automated system that processes used clothing for high-quality textile recycling using AI and laser technology. The goal of this system is to transform post-consumer clothing into high-quality, reliable feedstock, addressing the fact that recyclers currently suffer substantial production yield losses ($7.5B) due to bad feedstock [100]. The system begins with a conveyor-fed imaging station where three specialised cameras generate a high-resolution, multi-dimensional map of the garment, enabling fibre composition analysis down to the millimetre level [100].

The system leverages artificial intelligence and machine vision to identify and remove non-recyclable elements from clothing, including zippers, logos, and mixed materials. This capability addresses a significant challenge in textile recycling, as these components often contaminate recycling streams and reduce the quality of recycled materials [96]. The AI algorithms interpret infrared reflections to define fibre type and identify features like collars and cuffs, then pass this data to a robotic laser-cutting system that removes non-recyclable elements with precision without damaging reusable material. Once processed, the cleaned materials are sorted into separate bins for recycling, creating high-quality feedstock that can be reintegrated into manufacturing processes [100].

3.4.2 INTEGRATION WITH RECYCLING INFRASTRUCTURE

The effectiveness of AI-enabled textile recycling depends on seamless integration with existing and emerging recycling infrastructure. The RIT system demonstrates this integration through collaborations with industry partners including Nike, Goodwill, and Ambercycle, a company pioneering polyester recycling. This collaborative approach ensures that the technology addresses real-world challenges and can be scaled effectively across different recycling contexts [100].

Operating at approximately one garment every 10 seconds, this automated approach offers significant improvements over conventional sorting, which is labor-intensive and suffers from inefficiency and human error [89]. Although this technology was built considering its scalability to be both economical and replicable, scaling these advanced technologies in general, which utilize AI, multiple cameras, and a robotic laser-cutting system, requires a high initial investment cost [95,100]. Therefore, despite the benefit that these technologies offer, long-term economic viability and cost-benefit analysis must carefully weigh the high investment in sophisticated technology. A detailed synthesis of AI technologies, key achievements, sustainability benefits, and real-world examples across textile manufacturing and circular economy solutions is provided in Table 2.

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Table 2: AI Applications in Sustainable Textile Manufacturing

Application Area	AI Techs	Key Achievements	Sustainability Benefits	Paper Study Cases / Real-World Example	Ref.
Predictive Maintenance	AutoML, H2O	Achieved an R^2 of 0.73 for predicting yarn break prediction led to more than 30% reduction in unplanned downtime; 19% improvement in overall reliability; 18% decrease in maintenance costs.	Reduces downtime; optimizes manufacturing processes.	Predictive model was deployed at a Portuguese textile company to predict weft breaks; Another case study in Jaya Shree Textiles (India); Adopting Microsoft Fabric platform over a 90-day trial in a manufacture.	[56–59]
Color Matching (Process Opt.)	Ant Colony Optimization (ACO), ANN	Successfully predicted optimal dye recipes; minimized color deviation between cotton and polyester blends.	Reduces water, energy, and chemical consumption; minimizes resource-intensive re-dyeing.	ACO algorithms reduced the need for multiple colour corrections and subsequent wastewater generation by finding the right combination of reactive dyes.	[14,60,61]
Quality Control	Computer Vision, Deep Learning	Achieved more than 90% accuracy; speeds up to 60 metres/minute; led to a 25% improvement in defect detection.	Reduces material waste (by approximately 20% in large-scale facilities); prevents costly rework operations.	Systems like WiseEye, ISRA Vision GmbH, Advantech Automated Optical Inspection (AOI), and Robro Systems' KWIS as major providers with up to 99% detection accuracy.	[64–66,70–74]
Sustainable Production Planning	LSTM, Reinforcement Learning (RL), Natural Language Processing (NLP)	Reduced forecasting errors by up to 25%; contributes to a reduction in unsold finished goods.	Ensures production volumes closely match consumption needs; avoids overproduction and inventory waste.	20% reduction in unsold finished goods by applying AI-powered social listening in Zara; 70% of re-buys being driven by using NLP in Stitch Fix; Managing time-to-market for new collections by using NLP in Tommy Hilfiger.	[76–83]
Automated Textile Sorting	CNNs, Hybrid Models, Computer Vision	Achieved classification accuracy up to 100% for pure fibres (under controlled conditions).	Essential for accurate material identification; critical for maintaining the quality and value of recycled materials.	An innovative digital sorting solution using image recognition and AI in Circular.fashion.	[89–91]
Condition Assessment for Second-Life Markets	Computer Vision, AI	Detects subtle signs of aging and damage, such as colour fading, pilling, and surface abrasion.	Provides objective, consistent evaluation for reuse; enhances consumer trust; extends garment	precise results in luxury resale in Vestiaire Collective; manage traceability data necessary for Digital Product Passports (DPPs) in	[92–94]

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			lifespan through facilitated reuse.	TrusTrace.	
Recycling Process Optimisation / Design for Disassembly (DfD)	ML Algorithms, Generative AI, Robotics	Predicts the behaviour of composite materials during recycling processes; suggests design modifications that enhance recyclability.	Enables more efficient recovery of valuable components, including precious metals; supports modular design for easy separation.	Suggesting design modifications (like standardizing material combinations) by multi-objective optimization.	[95–98]
Automated Garment Dismantling	AI, Machine Vision, Robotic Laser-Cutting	The prototype system can process a new garment approximately every 10 seconds; identifies and removes non-recyclable components (zippers, logos) with precision.	Transforms post-consumer clothing into high-quality, reliable recycling feedstock; addresses the industry problem of production yield losses ($7.5B) due to bad feedstock.	RIT's system using specialized cameras and AI to map garments and guide a robotic laser-cutting system to remove non-recyclable contaminants.	[89,100]

4 DISCUSSION
4.1 CHALLENGES AND LIMITATIONS

Despite the significant advancements and promising applications of Artificial Intelligence in transforming textile sustainability, several challenges remain that must be addressed to fully realise AI's potential in advancing circular economy principles. This section examines these limitations, proposes future research directions, and provides concluding remarks on the evolving landscape of AI-driven sustainability in the textile industry.

4.1.1 TECHNICAL AND IMPLEMENTATION CHALLENGES

The widespread adoption of AI in the textile industry faces several significant technical and operational barriers. Data scarcity represents a fundamental challenge, as many AI models require large, diverse, and high-quality datasets for effective training and validation [7]. This scarcity is rooted in complex systemic challenges, including the reluctance of companies to share proprietary or commercially sensitive information due to ownership or trust issues. Furthermore, textile industry players and contributors have different data management capacities, which in many cases low digital maturity has made the data handling and documentation processes throughout the textile value chain highly difficult. This prevents the harmonization and standardization needed for efficient transfer across systems [102]. In addition, carefully labelling datasets is labour-intensive and costly [103]. Current datasets for textile applications are often limited in size and scope, with most research focusing on fabric swatches (20 studies) rather than whole garments (only 7 instances) [7]. This limitation affects model generalisability and real-world performance across diverse textile types and complex scenarios.

Additionally, the black-box nature of many complex AI algorithms, particularly deep learning models, raises concerns about interpretability and trust among industry stakeholders who require transparent decision-making processes [103]. The primary response to this issue is the widespread adoption of Explainable Artificial Intelligence (XAI) techniques like LIME and SHAP. These methods are designed to generate post hoc explanations to help users understand the output of black box models [104]. However, these generic XAI tools are often "inadequate to be directly used" in complex manufacturing environments. This insufficiency arises because their underlying mechanisms, such as LIME's image perturbation, can "mislead the underlying model" and yield "poor explanations" by introducing artifacts that models confuse with actual defects [105]. Furthermore, SHAP's utility may be limited in "complex, interconnected systems" (such as dynamic production processes) due to its

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assumption of feature independence [104]. Therefore, where XAI methods are insufficient, the definitive approach suggested by the sources is Causality Analysis or Causal Discovery, which provides a "transparent white-box model" where causal relations are explicitly known. This technique offers a deeper understanding beyond mere feature importance by uncovering cause-and-effect relationships, empowering domain experts to identify the root causes of variations, track changes in process dynamics through interpretable causal graphs, and ultimately enable proactive intervention [104].

Implementation challenges include the high cost of AI integration, which is financially prohibitive for many organizations, demanding substantial upfront investments and extensive resources, thereby limiting accessibility especially for small and medium enterprises [103], and the compatibility issues between advanced AI systems and existing manufacturing infrastructure, especially those textile sectors with very low digital maturity level [102]. Many fashion and luxury brands operate with costly legacy systems that are rigid, not scalable, and have restricted data warehouses, which struggle to incorporate new data sources [102]. Furthermore, the rapid evolution of AI technologies creates a skills gap in the textile workforce, as specialised expertise is required to develop, implement, and maintain these systems effectively [102].

For smart textiles and textronics containing electronics, additional challenges emerge regarding end-of-life management and recycling complexities. The integration of flexible electronics, conductive polymers, and sensors creates hybrid materials that are difficult to disassemble and recycle using conventional methods. The presence of these electronic components, which often contain hazardous materials such as heavy metals or toxic chemicals, along with the diversity of material combinations, poses significant challenges for waste management and threatens to exacerbate the growing problem of e-waste if not properly addressed through circular design principles. These principles must include modular design to ensure electronic components and fabrics are easy to separate [96].

4.1.2 ECONOMIC AND SOCIAL CONSIDERATIONS

Beyond technical challenges, the integration of AI in textile sustainability raises important economic and social considerations. The economic viability of AI solutions remains a concern, particularly for small and medium enterprises (SMEs) that may lack the capital for significant technological investments. While AI offers long-term cost savings through efficiency improvements and waste reduction, the initial investment required for AI infrastructure, training, and development can be prohibitive for smaller players in the industry [103,106]. This economic barrier, could potentially risk concentrating advanced AI technology adoption within larger enterprises, thereby widening the gap between large enterprises and SMEs within the innovation ecosystem and leading to MSME marginalization [107]. To address this structural and financial disparity, specific solutions are necessary to democratize access: Technologically, the high cost of implementation can be mitigated through the adoption of cloud computing and the strategic adoption of affordable AI-as-a-Service (AIaaS) models without initial equipment investment [108]. Structurally and through policy, governments must provide targeted financial incentives such as tax breaks or grants to encourage AI adoption, especially for SMEs [107,109]. Furthermore, establishing regional innovation hubs and public-private partnerships can reduce geographic disparities in adoption by centralizing funding, technology, and expertise [107]; a notable example of such efforts aimed at innovation in the textile sector is the Advanced Functional Fabrics of America (AFFOA).

Social implications include potential job displacement as automation reduces the need for manual labour in areas such as quality inspection, sorting, and some aspects of manufacturing. The transition to AI-driven processes may marginalise workers with traditional textile skills while creating demand for new technical expertise [107]. However, the net effect is complex because AI is also likely to complement human work, requiring a shift to a new labour structure. This transformation fosters a high demand for new technical expertise, specifically roles for AI/ML specialists and data analysts, and necessitates cognitive skills like creative problem solving and collaboration in hybrid human-robot teams [110]. This structural change mandates investment in workforce retraining and skills development to ensure a just transition toward more sustainable production models [108]. Additionally, there are concerns about the environmental footprint of AI technologies themselves, including the energy consumption of data centres and computing resources required for training and operating complex models, underscoring the need for energy-efficient algorithms and sustainable infrastructure [103].

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4.2 FUTURE RESEARCH DIRECTIONS

Several promising research directions emerge to address current limitations and advance the application of AI for textile sustainability. There is a critical need for larger and more diverse datasets that encompass varied textile types, conditions, and production scenarios. Collaborative efforts between industry and academia could facilitate the creation of standardised, open-source datasets following FAIR (Findable, Accessible, Interoperable, Reusable) principles [111], to accelerate model development and benchmarking.

The development of physics-informed neural networks represents a promising approach to enhancing model robustness while reducing data requirements. By incorporating domain knowledge and physical principles into AI architectures, these models can improve generalization to unseen conditions and provide more reliable predictions [112]. Additionally, research should focus on explainable AI techniques that enhance model interpretability, building trust among manufacturers and consumers while providing valuable insights into the relationships between material composition, processing parameters, and final properties.

Future efforts should also prioritise AI-driven design for circularity, developing systems that optimise not only for performance and cost but also for recyclability, disassembly, and material health. This includes creating digital product passports that track composition and facilitate sorting, as well as generative AI tools that suggest designs minimising waste and enabling easier material recovery. Research into AI-assisted development of mono-material textiles with maintained functionality could significantly enhance recyclability while meeting performance requirements. This potential is strongly supported by successful Design for Recycling (DfR) applications in the plastics industry, where converting multi-material components into mono-material solutions has been shown to enhance recyclability, maintain the required functionality, and result in substantial environmental and economic reductions [113].

One significant future research direction lies in the development of a fully integrated multi-modal AI framework that bridges the gap between end-of-life sorting and real-time life cycle assessment (LCA). While multi-modal AI models combining computer vision, sensor data (e.g., hyperspectral imaging), and digital product passports (DPPs) are showing promise for robust sorting, their impact can be amplified by coupling these insights with dynamic LCA. This integrated approach would allow an AI system not only to make optimal sorting decisions based on material composition and origin, but also to provide real-time environmental impact data that quantifies the sustainability benefits of specific recycling pathways. Such a system could automatically update LCA models with real-time end-of-life processing data, moving beyond traditional, static assessments to create a dynamic feedback loop that continuously informs and improves circular economy strategies for textiles. This combined effort would accelerate data collection, enhance accuracy, and provide designers and manufacturers with actionable insights on the true environmental costs and benefits of their choices.

4.3 POLICY AND IMPLEMENTATION FRAMEWORK

The successful integration of AI for textile sustainability requires supportive policy frameworks and implementation strategies, which must be specifically structured around circular economy drivers such as Extended Producer Responsibility (EPR) schemes. Governments and industry bodies can play a crucial role in facilitating this transition through targeted interventions such as research funding, standards development, and incentive structures like eco-modulated fees that financially reward producers who utilize AI to promote circularity, such as developing AI-optimized DfR. A cornerstone of this policy must be the mandatory adoption of advanced labelling strategies, including Digital Product Identification or digital product passports, to ensure textile traceability and provide comprehensive data. Policies that encourage data sharing to enable efficient downstream applications while protecting intellectual property could accelerate the development of comprehensive datasets needed for robust AI models.

Implementation frameworks should address the specific needs of different stakeholders across the textile value chain. Specifically, governments must advocate for public procurement policies that prioritize textiles verified by AI-driven sustainability and circularity metrics. This approach creates a guaranteed market for early adopters of AI technologies, helping to mitigate the high costs and uncertainties regarding Return on Investment (ROI) that often deter implementation, especially for SMEs. This Green purchasing policy can require public agencies to procure environmentally preferable products. For

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manufacturers, guidelines for phased AI adoption that minimise disruption and maximise return on investment would facilitate broader implementation. For recycling facilities and second-hand markets, standards for AI-based quality and condition assessment could create more transparent and efficient markets for used textiles. Educational institutions have a role to play in developing curricula that bridge textile science with data analytics and AI competencies, preparing the next generation of professionals for the evolving industry landscape.

Table 3 synthesizes the major challenges, necessary future research directions, policy frameworks, and underlying context for the sustainable integration of AI in the textile sector.

Table 3: Challenges and Future Directions for AI in Textile Sustainability

Challenge Category	Specific Challenges	Future Research Directions	Implementation Considerations	Ref.
Technical Limitations	Data scarcity (limited size/scope); Model interpretability ("black-box" nature of DL); Generalization.	Development of PINNs to enhance robustness and generalization; Combining XAI techniques with Causality Analysis for transparent, white-box models; Synthetic data generation.	Collaborative development of large, diverse, open-source datasets (following FAIR principles); Model benchmarking standards.	[7,102,104]
System Integration & Implementation	High initial implementation costs; Compatibility issues with legacy equipment (low digital maturity).	Development of modular AI systems and retrofit solutions for older machinery; Increased adoption of cloud-based platforms (AI-as-a-Service, AIaaS).	Phased implementation guides to minimise disruption.	[102,103]
Circular Economy Applications	Recycling complexity of smart textiles (hybrid materials); Need for standardized material composition data.	AI-driven DfD; Generative AI tools to suggest designs minimizing waste and enhancing recyclability; Development of mono-material textiles.	Mandatory adoption of DPPs for traceability; Recycling compatibility labelling standards.	[96,113]
Economic Viability & Access	High initial investment is prohibitive for SMEs; Risk of innovation being concentrated in large corporations.	Targeted financial incentives (tax breaks, grants) for SME adoption; Establishing regional innovation hubs (e.g., AFFOA)	Eco-modulated fees that financially reward producers using AI for circularity; Public procurement policies prioritizing AI-verified sustainable textiles.	[107–109]
Social Implications	Potential workforce displacement from automation; Skills gap.	Research into Human-AI collaboration systems; Development of adaptive learning platforms.	Investment in workforce transition and skills development programs; Development of curricula bridging textile science and data analytics.	[107,110]
Environmental Implications	Environmental footprint of AI (energy consumption of data centres).	Focus on energy-efficient algorithms.	Sustainable infrastructure.	[103]

5 CONCLUSION

This review substantiates the considerable potential of Artificial Intelligence and Machine Learning to advance sustainability in the textile industry through a circular economy lens. AI-driven approaches facilitate unprecedented efficiencies, waste reduction, and resource conservation across the value chain, from predictive material design and manufacturing optimisation to waste management and recycling. Key applications, including predictive modelling of material properties, computer vision for quality control and defect detection, and automated sorting for textile waste, are pivotal in building closed-loop systems that maximise resource value and minimise environmental impact. Innovations such as AI-driven Design for Disassembly (DfD) and robotic garment dismantling further underscore this potential.

A central finding of this review, however, is that whilst core AI methodologies demonstrate significant algorithmic efficacy, their realised impact on textile circularity is primarily constrained by systemic, non-algorithmic barriers. Realising AI's full potential necessitates addressing persistent challenges related to data availability—often rooted in commercial reluctance to share proprietary information and the low digital maturity of many textile operations. Moreover, high initial implementation costs and compatibility issues with legacy systems present significant economic and technical hurdles, which risk marginalising small and medium-sized enterprises (SMEs).

Consequently, future research should prioritise: (i) the development of more robust, physics-informed models to enhance generalisation with limited data; (ii) the collaborative creation of comprehensive, standardised, and diverse datasets; and (iii) enhancing the explainability and accessibility of AI tools to foster broader industry adoption. The successful transition of the textile industry towards circularity will depend not only on these technological advancements but also on supportive policy frameworks and the alignment of economic incentives with sustainability objectives.

As AI technologies mature, their deeper integration with textile science and engineering promises to unlock new frontiers for sustainable innovation. Harnessing AI for circular economy applications offers a pathway towards a more regenerative and efficient industrial model, balancing economic growth with environmental stewardship and social responsibility. This transformation represents not merely a technological imperative but an essential commitment to achieving global sustainability goals within an industry integral to modern society.

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