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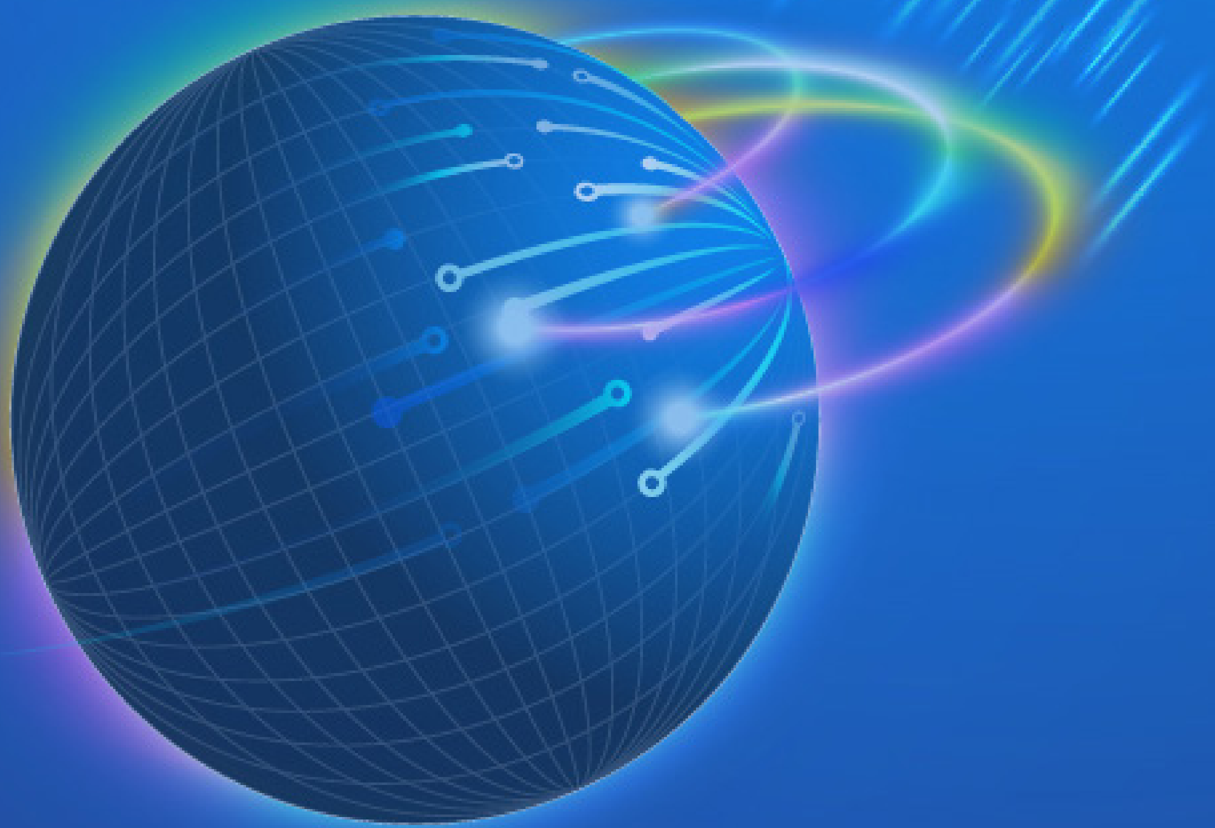

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Usages of AI in Waste Minimization and Recycling Strategies in Textile Manufacturing

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ABSTRACT

The purpose of this research was to assess the potential impact of Artificial Intelligence (AI) technology on the textile industry's waste-reduction and recycling measures. Primary data were collected through focused survey on package performance, interviews of production managers, quality control engineers, and sustainability officers working in different textile industries. The qualitative interviews were analyzed by way of thematic content analysis. The results show that weaving mills are the sector with the greatest total waste (93±7 kg per 1000 m² of fabric) and cutting of fabric is the main source of it in all the sectors. However, mechanical recycling process, then the chemical recycling and finally the waste to energy process is the major processes in marketing. AI adoption is driven by data analytics for process optimization (65.4±4.8% for garment manufacturing) and machine learning for predictive maintenance (55.2±3.1%), whereas AI for recycling and sorting automation exhibits lower adoption (28.6±2.8%). After AI implementation, garment manufacturing produced the highest total waste percentage reduction (17.1±3.1%) and total cutting waste reduction (20.8±3.4%). The rewards are also seeing are also identified being less wastage of materials by 72%, better efficiency within the production process by 68.4% and less machine rework by 62.5%. The highest barriers to AI deployment are costs of implementation (65.3±4.7% in garment manufacturing) and technical expertise (58.6±3.5%) highly cited, with staff training (68.1±5.1%) and financial incentives (55.7±4.8%) recognized as important fore-runners. In summary, combined with targeted waste reduction and recycling, the practice of AI is a viable route toward sustainable, efficient, and environmentally benign textile manufacturing.

INTRODUCTION

The textile industry is among the most environmentally punishing in the world, generating nearly 10 percent of global greenhouse gas emissions and a phenomenal amount of waste (Leal Filho *et al.,* 2022). A textile mill can use as much as 1.6 million liters of water to produce 8,000 kg of fabric, and only about 1 percent of the 180,000 tons of textile waste that the country generates annually is transformed into new garments (Mamun *et al.,* 2022; Nahar *et al.,* 2024). The rest is generally discarded in landfills or incinerated. Such shocking waste and inefficiency only serve to reinforce the requirement for radical new approaches to reduce resource consumption and increase circularity in our industry. Artificial Intelligence (AI) is being seen as a powerful catalyst to enable this transformation, with tools and methodologies to drastically cut waste across textile production and recycling (Bermeo-Giraldo *et al.,* 2025; Faghih *et al.,* 2025). AI is used in manufacturing to optimize pattern layouts and minimize scrap material. As AI based pattern optimization tools, including those reducing fabric waste by as much as 20 percent, particularly in cutting, where 15-20 percent waste are commonly found (Khairul Akter *et al.,* 2022). Beyond layout optimization, demand forecasting with AI also cuts overproduction by analyzing emerging trends, sales data and customer behavior, meaning less unsold inventory and waste to the tune of an equivalent drop in carbon emissions (Olamide Raimat Amosu *et al.,* 2024).

Other important application areas are in quality control. Visual inspection is a manual defect detection while being able to ignore some defects. In contrast, machine vision systems with AI processing, particularly those based on deep learning (Convolutional Neural Network) models, now allow for real-time inspection with much better levels of accuracy (Soori *et al.,* 2023). Such systems can spot fine defects invisible to the naked eye, cut wastage of fabric by as much as 20 percent, and raise the efficiency of production greatly (Ozek *et al.,* 2025). In the world of post-consumer waste, AI is transforming textile sorting the bottleneck of any recycling process. Hyperspectral imaging and computer vision harnessing AI can correctly determine fiber compositions, colors, and garment types, even when the latter are combined (Huang *et al.,* 2022). With the help of machine learning, companies are reading compositions so subtle, they can tell, for example when a garment contains 1 percent elastane, which results in more accurate sorting and more viable recycling streams. Academic research is driving these methods forward; supervised and unsupervised deep learning models for

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near-infrared (NIR) hyperspectral imaging are able to generalize well for textile classification, indicating promise in enabling more efficient recycling pipelines (Kainz *et al.,* 2025). On the industrial level, a new autonomous sorting pipeline combining robotics for sorting, spectral imaging for recognizing the characteristics, AI for classifying the object and modelling based on digital-twins, has proven to provide substantial improvements in sorting precision, efficiency and scalability – all important factors for sustainable textile recycling (Dodampegama *et al.,* 2024; Halvorsen *et al.,* 2025).

AI can also underpin chemical and biological recycling routes. AI and synthetic biology in the creation of enzymes that will degrade and blend nylon and polyester waste into recyclable monomers, thereby creating recycling loops that could go on indefinitely (Enking *et al.,* 2025). Meanwhile, firms are creating breakthroughs in chemical recycling techniques like depolymerization and repolymerization to recycle polyester waste back into virgin-quality material, but the feedstock supply and separation effectiveness still pose the challenges (Wang *et al.,* 2025). Together, these AI-led breakthroughs are transforming the textile industry, empowering smarter design, production, sorting, and recycling. They are a key part of a circular economy, which is designed to keep products and materials in use for as long as possible, and to reuse resources again and again (Khairul Akter *et al.,* 2022). Digital technologies (such as AI) are increasingly nominated as an enabler of the circularity concept through improving resource efficiency, traceability and process optimization (Gazzola *et al.,* 2025).

LITERATURE REVIEW

The global textile industry, a major player of the economy of countries directly, is one of the most challenging environmental problems in the world as well, because it uses so many resources and generates a huge amount of waste in every part along the value chain (Biyada & Urbonavičius, 2025). Starting from the extraction of raw material to final disposal, textile goods production generates huge amount of solid waste, waste water, and air pollutants, which results in land fill pressure, water pollution, and green house gas emission (Niinimäki *et al.,* 2020). Linear models for the production and consumption are not viable anymore and there is a need for a transition to the circular economy principles focusing on minimizing waste and maximizing recycling efficiencies. In this light, Artificial Intelligence (AI) becomes an enabling technology which provides revolutionary advantages for process optimization and decision making and the development of new solutions on what concerns the reduction of waste and the recovery of resources in the very complex textile industry (Snoun *et al.,* 2025).

The Scale of Textile Waste and Environmental Imperatives

The amount of textile waste produced at global level is overwhelming, as few as 1% of all clothing waste is effectively recycled into new textiles (Biyada & Urbonavičius, 2025). Most of it ends in landfills, or is simply burned, causing land, water, and air degradation (Tang, 2023) as a result of leaching dyes and chemicals, and the resulting emission of green-house gases. In addition to post-consumer waste, pre-consumer waste produced during pre and on production stages, as off-cuts from pattern cutting, defective products, and overproduction have considerable waste (Haq & Alam, 2023; Imran *et al.,* 2024). Fast fashion product (defined by short cycle times, low prices, and high levels of consumption) has further exacerbated the problem with shortened product life and significant increase in textile waste (Morgan & Birtwistle, 2009). The complex issue of addressing this waste is a pressing environmental requirement but, at the same time, an economic opportunity, and it's this that has spurred the quest for alternative solutions, in which AI is coming more and more into favor.

Traditional Approaches to Waste Minimization and Recycling

In the past, waste minimization activities in the textile industry have been primarily focused on lean production, process optimizations, and inventory control (Khairul Akter *et al.,* 2022). The classical recycling of fibres may proceed by mechanical fibre recycling (hammer milling of fabric into fibres, mostly for low-value applications) or chemical recycling that breaks down fibres into their polymer monomers (Sandin & Peters, 2018). Although these approaches are partially successful, they are limited inherently. The manual component in waste separation process is intensive, time consuming, and done in error-prone manner making it difficult to efficiently reclaim high-quality materials (Singh *et al.,* 2023). Optimization of the process is typically based on empirical fits or process statistical control, which may not account for complex non-linear behavior, change over time, and consequently this leads to sub-optimal material use (Samadiani *et al.,* 2024). Also, insufficient waste category and material content data effectively obstructs recycling decision-making. It is due to these limitations that the mandate for advanced computational techniques that can sift through thousands of results and interpret complex patterns to make intelligent predictions is, and by all accounts should really be, addressed by AI.

AI in Waste Minimization Strategies

Design and Pre-Production Optimization

Systems induced by AI can have a large impact on reducing waste from the start of design. Generative design AI can help designers to generate patterns with increased fabric efficiency, reducing off-cuts and improving the likelihood of more optimal nesting (Peckham *et al.,* 2025). Machine learning approaches can process large datasets of material properties, production limitations and end-of-life treatments to recommend sustainable and recyclable material selections, incorporating circularity from the early design phase (Raut *et al.,* 2025). Predictive analytics serve to predict demand better, minimizing overproduction and dead stock, a leading cause of waste in the fashion industry (Gazzola *et al.,* 2025). With production planning tuned to real-time sales figures and customer demand, the AI can help synchronize supply with demand and minimize the need to mark down unsold inventory or discard it (Praveen Kumar *et al.,* 2024).

Production Process Optimization

AI can also optimize the process of manufacturing itself to minimize waste of material and energy. Computer vision and machine learning can be used for on-the-fly quality assurance in production lines, in order to detect defects in production processes as early as possible, and avoid waste of entire batches (Chen *et al.,* 2023). AI-based predictive maintenance systems forewarn equipment failures, minimizing downtime and waste when machinery is malfunctioning (Lee *et al.,* 2019). Artificial intelligence can be used to tailor levels of chemicals, temperature, and timing involved in the dyeing and finishing process, which can reduce the use of water, chemicals and energy, and help ensure quality (El Khaoudi *et al.,* 2024). In addition, AI-based robotic cutting systems with modern nesting software can achieve better fabric utilization rates than manual or automatic cutting process, much less than non-automated cutting systems, which means much less textile waste (Wang & Wang, 2020).

Supply Chain and Inventory Management

It's not just on the factory floor, AI goes way beyond to optimize the entire supply chain. By learning from sales histories, changes in the market trends, effects of the weather, or analyzing the sentiment in the social media for a brand, AI models can deliver high accuracy demand forecasts, which will allow the manufacturers to order only what will be actually needed and will help to significantly decrease overproduction and unwanted textile waste produced or resulting from that overproduction (Olamide Raimat Amosu *et al.,* 2024). This enhanced prediction capability also involves raw materials purchasing, avoiding over purchasing and reducing waste during storage. Artificial intelligence enabled real-time inventory tracking and optimization mad handling of materials and finished goods efficient leading to reduced losses on account of dam age, obsolescence or expiry (Çaylı & Oralhan, 2024).

AI in Recycling Strategies

Automated Material Sorting and Identification

The separating of various types of mixed textile waste on the basis of fiber type (e.g., natural, synthetic, chemical) and color will be one of the most difficult tasks to accomplish economically and precisely during the recycling process (Chen *et al.,* 2023). Conventional manual sorting is due to be hard, inefficient, and is not able to meet the massive amount of waste. Computer vision based AI solutions, as well as spectroscopic (e.g., Near-Infrared Spectroscopy) technology, are transforming this method. Large textile image and spectral datasets can be used to create machine learning models that efficiently and accurately classify independent fiber types (cotton, polyester, nylon, blends, etc.) and source location (Huang *et al.,* 2022; Liu *et al.,* 2020). This automated and error-free sorting is essential for the economic efficient recycling of the future, especially with regard to chemical recycling processes with homogeneous material flows.

Quality Control and Characterization of Recycled Materials

Consistency and quality of recycled fibres and materials are essential for their adoption in new products. This is where AI comes into play and can provide much smarter quality checks. Machine-learning models could then be trained to study the characteristics of recycled pulp or mill broke fibers and predict their mechanical properties, spinnability, and final application ((Rezvan *et al.,* 2023). This early-stage quality control ensures sustainability of the recycled material's value and helps manufacturers to have certainty in integrating it into their manufacturing processes, more effectively facilitating to close the loop (Albuquerque *et al.,* 2025).

Optimization of Recycling Logistics and Supply Chains

Effective collection, transport and processing of waste streams are critical to the effectiveness of textile recycling. AI can optimize the "reverse logistics supply chain" for tags recycling of the waste collected (Copara *et al.,* 2025). This includes predicting the optimum waste collection path of waste collection vehicles, predicting the trend of wastage hotspots, and determining the aggregation points. AI-driven optimization algorithms can benefit from dynamic logistics planning with real-time information of waste would be ready, collection capacity, recycling facility demand, and so on, and to minimize transport costs and environmental footprint, thus recycling can be done in an economically sustainable and scalable way (Alsabt *et al.,* 2024; Dao *et al.,* 2025).

Challenges and Limitations of AI Adoption

While enormous potential exists, several obstacles for broad AI application in textile waste reduction and recycling are present. Availability and quality of data are of utmost importance; AI models need large, diverse and clean dataset to train effectively, which is hard to build over the fragmented textile supply chains (Olawade *et al.,* 2024). Adoption of AI in textile factory and the whole supply chain requires overcoming these challenges of AI technology packages and the interfacing between AI and the legacy systems (Ahmad *et al.,* 2020). In addition, there is a lack of talents with cross disciplines, i.e. textile engineers with the knowledge of AI and data science, that can slow down the fast and efficient development and application (Bhandari *et al.,* 2022; Brewer, 2019).

Research Gap

Although there is increasing interest in environmentally sustainable production, integration of AI in textile waste minimization and recycling is relatively unexplored. Most of these studies concentrate either on general AI applications in the context of industrial automation, or on traditional approaches to waste management in the textile sector, they do not systematically investigate the impact of AI for reducing material wastage and optimizing the recycling process. Moreover, the effectiveness of some AI technologies such as machine learning, computer vision and robotic process automation in the context of textile production has not been empirically examined in depth. In addition, obstacles to adoption such as large resource requirements, technical complexity and a lack of know-how are not clearly studied. Therefore, there is a demand for a solid study to not only characterize AI modes of operation for waste minimization but to likewise assess the practical success, challenges and generalizability of such strategies in varying types and scales of textile manufacturing units.

Research Questions

a) What waste is being generated and recycled in the textile manufacturing at present?

b) What AI technologies are being used for waste reduction and enhanced recyclability in producing textiles?

c) To what extent AI-based tools and solutions allow to minimize wastage and manage processes in recycling efficiently?

d) What are the main obstacles and challenges that hinder textile producers from adopting AI for waste reduction?

e) Does company size, production gradient or textile activity type affect the adoption and the effectivity of AI-based waste management strategies?

Research Objectives

a) To evaluate the current status of waste management and recycling in textile manufacturing sector.

b) To recognize and assess AI technologies used in waste reduction and recycling.

c) To assess the potential impact for AI driven solutions to reduce waste in textiles, and to increase recycling opportunities.

d) To study what are the hurdles and challenges to utilizing AI to promote sustainable waste management.

e) To determine the level of AI adoption and the effectiveness across textile companies based on size and scale of production.

MATERIALS AND METHODS

This study was based on descriptive-analytical methodology. Data were obtained from primary and secondary sources. Primary data was collected between January and December 2024 by means of focused surveys and interviews of production managers, quality control engineers, and sustainability officers belonging to the different textile industries. The questionnaire solicited information about existing waste management, AI implementation and challenges associated with implementing AI-based waste management solutions. In addition to cross-examination with primary data, secondary data on peer-reviewed articles, industry reports, case studies, and company sustainability reports were used to triangulate and confirm primary data.

The analyses concerned AI in the context of reducing textile waste, such as machine learning to prevent machinery dysfunction and predict maintenance, computer vision to enable automated inspection and sorting, data analytics to detect dumping patterns, and robotic process automation for recycling and logistics support. Intentional sampling technique was employed to recruit both large and small size textile companies participating in AI applications or sustainable practices. Descriptive statistics were applied to the quantitative survey data, and thematic content analysis was performed on the qualitative interviews. Differences in the adoption of AI and waste management on the basis of the size of the company and production scale were further analyzed through comparative analyses. Pre-tested survey instruments helped to ensure the validity and reliability of data, as well as cross-checking information obtained from the secondary sources and involving of experts for validation of interpretations. The administration of the questionnaires and the company-specific information were confidential and institutional requirements for informed consent were preserved.

Analysis and Results

Current Waste Generation and Management Practices

Garment manufacturing produced a total waste of 87±6 kg per 1000 m² fabric (Table 1), with fabric cutting (45.5±4.7) as the dominant contributor, followed by dyeing (29.5±4.2) and finishing (12±2.5). Knitting mills produced less total waste (70±5 kg per 1000m² fabric), with cutting (37.3±3.9) and dyeing (22.1±3.3) accounting for the largest amounts. In contrast, weaving mills showed the highest waste (93±7 kg per 1000 m² fabric) where fabric cutting was the most contributing (50.6±6.5) with substantial contributions by dyeing (27.4±5.1) and finishing (15±2.4).

Table 1: Average waste generation in textile production (kg per 1000 m² fabric).

Textile Sector	Fabric cutting waste	Dyeing waste	Finishing waste	Total waste
Garment manufacturing	45.5±4.7	29.5±4.2	12±2.5	87±6
Knitting mills	37.3±3.9	22.1±3.3	10.6±1.6	70±5
Weaving mills	50.6±6.5	27.4±5.1	15±2.4	93±7

In garment manufacturing, mechanical recycling is the most widely applied (60%), followed by chemical recycling (25%) and waste-to-energy conversion (15%) (Table 2). There is a different distribution in case of knitting mills since the mechanical recycling is more predominant (50%), followed by the chemical recycling (30%) and waste to energy (20%). In weaving mills, however, waste-to-energy conversion takes a stronger role (35%) compared to the other sectors, though mechanical recycling remains the leading method (45%), while chemical recycling is applied the least (20%).

Table 2: Recycling practices adopted by textile firms (%).

Recycling Method	Garment manufacturing	Knitting mills	Weaving mills
Mechanical recycling	60±3.7	50±3.1	45±3.3
Chemical recycling	25±2.1	30±2.6	20±2.5
Waste-to-Energy conversion	15±1.9	20±2.2	35±2.8

Adoption of AI Technologies

In garment manufacturing, data analytics for process optimization is the most widely used (65.4±4.8), followed by machine learning for predictive maintenance (55.2±3.1) and computer vision for defect detection (50.8±4.7), while robotic process automation (RPA) has the lowest adoption (30.9±2.9) (Table 3). The use of data analytics (50.6±3.7), machine learning (40.5±3.6), and computer vision (35.9±2.8) in knitting mills is high and it is not as extensive for robotic process automation (25.2±2.4). Likewise, among the three textile sub-sectors, the adoption rates are lowest on average in weaving mills

Table 3: AI technologies implemented in textile manufacturing (%).

AI Technology	Garment manufacturing	Knitting mills	Weaving mills
Machine learning (Predictive maintenance)	55.2±3.1	40.5±3.6	35.4±2.7
Computer vision (Defect detection)	50.8±4.7	35.9±2.8	30.7±2.5
Data analytics (Process optimization)	65.4±4.8	50.6±3.7	45.1±3.4
Robotic process automation	30.9±2.9	25.2±2.4	20.6±2.2

Process efficiency optimization shows the highest adoption rate (62.8±3.1%) (Table 4). Material defect detection is also widely applied (58.5±3.6%). In contrast, inventory and stock management (35.3±2.9%) and recycling and sorting automation (28.6±2.8%) are less frequently adopted.

Table 4: Areas of AI application in waste minimization.

Application Area	Frequency of adoption (%)
Material defect detection	58.5±3.6
Process efficiency optimization	62.8±3.1
Inventory and stock management	35.3±2.9
Recycling and sorting automation	28.6±2.8

Effectiveness of AI in Waste Reduction

The maximum reductions in garment production were found in cutting waste (20.8±3.4), dyeing waste (18.1±2.6) and finishing waste (12.3±2.9) with a subsequent total reduction of 17.1±3.1 (Table 5). Knitting mills realized relatively low reductions, the highest reduction was achieved by cutting (15.4±2.5) followed by dyeing (12.9±2.5) and finishing (10.6±1.5) suggested minuscule reductions (13.0±2.5). Weaving mills improves relatively balanced of cutting waste reduction (18.7±3.3), compared to dyeing (15.3±2.6) and finishing (14.3±2.2), resulting in overall reduction of 16.2±3.1.

Table 5: Average reduction in waste after AI implementation (%).

Textile Sector	Cutting waste reduction	Dyeing waste reduction	Finishing waste reduction	Overall waste reduction
Garment manufacturing	20.8±3.4	18.1±2.6	12.3±2.9	17.1±3.1
Knitting mills	15.4±2.5	12.9±2.5	10.6±1.5	13.0±2.5
Weaving mills	18.7±3.3	15.3±2.6	14.3±2.2	16.2±3.1

The most widely reported benefit is reduced material waste (72%) (Table 6). This is followed by improved production efficiency (68.4%) and better-quality control (62.5%). Additionally, lower operational costs (55.2%) and enhanced recycling efficiency (49%) were also recognized, though to a lesser extent.

Table 6: Perceived benefits of AI adoption (% Respondents).

Benefit	Respondents (%)
Reduced material waste	72±4.6
Improved production efficiency	68.4±3.9
Lower operational costs	55.2±3.5
Enhanced recycling efficiency	49±2.8
Better quality control	62.5±4.1

Challenges and Barriers in AI Implementation

The greatest obstacle was high cost of implementation, which was the highest in the garment industry (65.3±4.7), knitting mills (60.4±4.2) and weaving mills (58.1±3.8) (Table 7). Technical skills were also of concern, especially in garment manufacturing (58.6±3.5), followed by knitting mills (55±3.9) and weaving mills (52.7±3.5). Integration with current systems was average-difficulty, ranging from 50.7±3.9 in garment manufacturing to 45.5±3.6 for knitting mills. On the other hand, lack of awareness about benefits of AI was found to be the least barrier towards AI adoption, but low across all at 42.1±3.2 for garment manufacturing and 38±2.5 among weaving mills.

Table 7: Key barriers to AI adoption in textile manufacturing (%).

Barrier	Garment manufacturing	Knitting mills	Weaving mills
High implementation cost	65.3±4.7	60.4±4.2	58.1±3.8
Lack of technical expertise	58.6±3.5	55±3.9	52.7±3.5
Integration with existing systems	50.7±3.9	45.5±3.6	47.4±2.9
Limited awareness of AI benefits	42.1±3.2	40.7±3.5	38±2.5

Table 8 proposed key initiatives to address the limitations to the adoption of AI in the textile industry. Training and skill development for staff was the most supported activity (68.1±5.1%). Financial incentives or subsidies were also considered important (55.7±4.8%). Furthermore, collaboration with AI solution providers (50.9±5.6%) were seen as actionable way to ease the process of adoption and integration. Programs and workshops on consciousness, however, were viewed as interesting but relatively underemphasized (47.3 ± 3.2%).

Table 8: Measures proposed to enhance AI adoption (%).

Measure	Respondents (%)
Staff training and skill development	68.1±5.1
Financial incentives/subsidies	55.7±4.8
Collaboration with AI solution providers	50.9±5.6
Awareness programs and workshops	47.3±3.2

Discussion

The results indicate a wide difference of waste generation between different textile industries, the weaving mills generating the largest overall quantity of waste and the garment production sector and the knitting mills following it. In each survey, fabric cutting is revealed to be the highest source of waste, consistent with past researches that revealed that the wastage of cutting from inefficient lay plan and offcut as a major source (S. Rahman & Uddin, 2022). The dyeing sector has relatively high waste generation as compared to other sectors, finds to be in accordance with that of Sharma *et al.* (2021) who highlighted the fact that dyehouse activity produces not only solid wastes, but is also a major source of both chemical and water pollution. It is also worth noting that finishing did not produce as much waste as cutting and dyeing, as evidenced by Liu *et al.* (2020) also reported that end-use tends to generate less waste in terms of percentage, yet potentially has greater contamination risk relative to chemicals waste. The relatively low waste level for the knitting mill could result from a relatively higher material efficiency during production than the waste level for garment manufacturers, as Farooq & Zhang (2021) argue that knitting methods frequently make use of continuous yarns with low cut to waste. Mechanical recycling is also the most practiced disposal option in all textile domains and subsectors such as, garment manufacturing followed by weaving which is consistent with other studies showing mechanical recycling cost efficiency and technical viability in handling post-industrial waste (Shamsuzzaman *et al.,* 2025; Sharma *et al.,* 2021). Chemical recycling is less widely used overall, but widely used in knitting mills (30%), in agreement with (Zhang *et al.,* 2018) remarked that chemical means are preferred when fiber recovery or quality enhancement is necessary. In the case of garment and knitting mills, the percentage contributions from waste towards energy recovery are relatively less (15-20%), except that of weaving mills (35%) probably due to the generation of large quantities and a variety of waste. The observation above is consistent with the results obtained in Liu *et al.* (2020) showed that energy recovery is preferred for sectors that generate textile waste that is mixed or less recyclable.

Data analytics-based process optimization is the most popular technology across textile sectors (mainly in garment sector), indicating its efficiency in improving process efficiency and savings in operative cost. Similar results were found by Sharma *et al.,* (2021) and Ribeiro *et al.* (2023), who reported that one of the significant predictors of productivity of textiles industry was data-driven decision-making. Machine learning (ML) for predictive maintenance and computer vision (CV) for defect detections are cumulatively adopted at a medium level in line with the findings by Liu *et al.* (2020) who reported that these AI techniques are being adopted more and more to reduce downtime and enhance product quality, with the drawback being that the technical expertise and investment in them need to be increased. The adoption rates of RPA are lower than other technologies across industries, indicating potential barriers like high initial investment and integration problem, which are also supported by Rahman & Uddin (2022) and Yang *et al.,* (2024). Furthermore, the largest purpose of automation is enhancing operating efficiency indicating that the majority of textile companies plan to cut production time, minimize errors, and maximize overall efficiency (Teshome *et al.,* 2024). This observation agrees with previous literature that pointed out process optimization using AI and automation as one of the main productivity-enabling factors in the textile industry (Kumar *et al.,* 2024; Sharma *et al.,* 2021). Material defect identification is also relatively well accepted, consistent with that reported by Zhang *et al.* (2020), pointing towards the fact that automated defect inspection optimizes quality control and diminishes waste resulting from faulty goods. Inventory and stock management and recycling and sorting automation are adopted less, possibly because they come with higher implementation cost and integration challenges, as also described by Liu *et al.* (2020).

The greatest waste reduction value of overall waste was observed for clothing production, followed by dyeing and cutting wastes. This is in accordance with prior research works that precise cut and dyed interventions, such as optimal pattern layouts and dye management systems, are more feasible and ideal for reducing waste (Rahman, 2022; Sharma *et al.,* 2021). The knitting mills had comparatively less total reductions (13.0±2.5%) and the finishing waste had little added impact; they have more basic production processes compared with the other two sectors and were shown to have already efficient material use other by Zhang *et al.* (2020). The weaving mills gained relatively more balanced improvements in all stages (in an average decrease of 16.2±3.1%), which is in consistent with Azanaw *et al.* (2022), who emphasized that full process optimization in cutting, dyeing and finishing leads to an extensive and homogeneous reduction of waste in industries that produce the most significant and varied waste streams. Material waste is the most obvious advantages in reducing material waste and process optimization (72%), previous research stated that reduction of waste should be the main goal to achieve both sustainable and showing cost benefits in textile manufacturing (Rahaman *et al.,* 2024; Sharma *et al.,* 2021). Increased production efficiency (68.4%) and better quality control (62.5%) improvement rates were also high, similar to in Gavrila Gavrila *et al.* (2023), where it was pointed out that automation and process optimization lead to higher throughput levels without compromising the quality of products. Lower operating costs (55.2%) and better recycling (49%) are also less cited but still important attributes, again confirming the findings of Liu *et al.* (2020), who indicated that recycling more effectively or saving energy expenses bring future economic and environmental advantages.

High implementation cost is reported as the most important impediment towards waste minimization and automation strategies, especially in garment manufacturing, in line with studies arguing cost constraints are critical inhibitors for technology adoption in the textile industry (Rahaman *et al.,* 2024). Insufficient technical knowledge was also among the key issues that arose, and aligns with the fears of advanced machines and AI-based systems as found in Zhang *et al.* (2020), who found that workforce skills often restrict successful technology adoption. Ease of integration with the main infrastructure was seen to be moderate difficult across the sectors which agree with the study of Liu *et al.* (2020) who argued that legacy infrastructure, and interoperability issues can limit the transition to automated and AI-based solutions. Low awareness of AI advantages, although reported less often was present and suggests that specific targeted training and awareness efforts are required to increase understanding and acceptance of emerging technologies (Sikka *et al.,* 2024). The policy with the highest mean score as well is support employees for training and skills upgrading, which is consistent with the results of studies that highlighted workforce training and capability building as essential for such revolutionary technologies to create impact (Zhang *et al.,* 2020) and financial incentives or subsidies in addressing high implementation cost, as identified by Rahman *et al.* (2022). The next most feasible strategy was to work with AI solution providers, which was also aligned with previous research, as external expertise may help overcome integration issues and support adoption of new technologies (Rashid & Kausik, 2024). Awareness programs and workshops, despite that has less centrality, but are an important option for building expertise on the benefits of AI and cultivating acceptance among industry stakeholders.

Findings

a) Weaving mills generated the greatest overall waste (93±7) followed by garment manufacturing (87±6), and knitting mills (70±5). Cutting room was always the largest wastage holder sector followed by dyeing and finishing.

b) Mechanical recycling was the most common strategy used, especially in garment production (60%) and weaving (45%).

c) Chemical recycling predominated in knitting mills (30%), while generation of waste-to-energy was the most pronounced in weaving mills (35%).

d) The most frequently used automation strategies were process efficiency optimization (62.8±3.1%) and product defect identification (58.5±3.6%).

e) The greatest overall waste reduction was obtained by garment manufacturing (17.1±3.1%), followed by those observed in weaving mills (16.2±3.1%) and knitting mills (13.0±2.5%).

f) The most common benefits reported were reduced material wastage (72%), improved production efficiency (68.4%) and better quality control (62.5%).

g) High implementation cost was the main obstacle, especially in the garment industry (65.3±4.7%), followed by the absence of technical know-how and low integration barriers.

h) Staff training and capacity building (68.1±5.1%), financial incentives contributed by subsidies (55.7±4.8%) and cooperation with AI solution providers (50.9±5.6%) were the top three most effective strategies.

Rrecommendations

a) Concentrate on optimization of cutting and dyeing process in knits, garment sectors, and co-optimization of cutting, dyeing and finishing in a weaving mill.

b) Scaling mechanical and chemical recycling methods adapted to the specific composition of each waste stream of the sectors. Areas generating mixed or less-recyclable residue should consider waste-to-energy conversion.

c) Give priority to the automation of efficiency improvement and defect detection. Work in the direction of stock control and automatic recycling when it is possible.

d) Develop a schedule of technical training programs that will provide staff with additional training in AI and automation tools. Promote cooperation with the AI solution vendor to realize smooth implementation of technology.

e) Undertake workshops, seminars and awareness programs for educating stakeholders in the benefits of AI and sustainable practices.

f) Create tracking mechanisms to quantify the amount of waste that is generated, how well it is reduced and how effectively it is recycled, which should lead to refinements and better policy.

CONCLUSION

The research findings indicate that AI-based policies and process improvement can significantly cut waste and increase the production efficiency and quality control of textile production, fabric cutting and dyeing being the major components of waste generation. Mechanical recycling was the most common method used but it was complemented by chemical recycling and waste-to-energy conversion when there were sector-specific requirements. Automation measures and a concentration on process efficiency and for detecting material defects clearly led to less wastage and to more stable operational productivity. However, obstacles such as high initial cost, low technical capacity, and challenge of integration are still dominant which emphasizes the effectiveness of staff training, financial incentives, and partner with the AI vendors and publicity campaign to facilitate adopting. Future studies could be directed towards advanced AI application through predictive analytics and real-time monitoring, lifecycle assessments for quantifying environmental and economic impacts, policy and incentive framework creation, knowledge transfer between sectors through cross-sector collaborations, and adoption of standardized sustainability metrics for continuous improvement. In conclusion, coupled with targeted waste reduction and recycling, applying AI is a realistic way toward sustainable, efficient, environmentally-friendly textile production.

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