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Towards Industry 4.0 in the Garment Sector: A Comprehensive Review on Applications of Machine Learning in RMG Industries

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Abstract

The ready-made garment (RMG) business is a big part of manufacturing and economic growth, especially in developing countries like Bangladesh. Nevertheless, it is still struggling with issues that include dependence on a manual workforce, lack of uniform product quality, and supply chain operations that are not efficient. An opportunity to overcome these problems by introducing Industry 4.0 technologies is transformative in nature as it allows automating and making decisions based on facts. The current paper provides a review of the implementation of a Machine learning (ML) throughout the whole cycle of manufacturing in RMG. This paper is a systematic investigation of the application of ML methods, such as Convolutional Neural Networks (CNNs), predictive analytics, and generative models to various major production processes, such as procurement of raw materials and inspection of fabrics, pattern making, cutting, sewing, printing, finishing, and final quality control. Furthermore, the paper examines how ML can be used in combination with other Industry 4.0 enablers such as the Internet of Things (IoT) and Big Data analytics to improve demand prediction, logistics, and retail feedback analysis. Although the advantages of ML in the RMG sector are promising, the implementation of ML is still piecemeal. The review summarizes the existing literature, outlines the existing gaps, and provides some of the recommendations to be made in the future in a bid to create the shift toward an intelligent, sound, and sustainable garment industry.

Keywords
Machine Learning, Industry 4.0, RMG, Smart Manufacturing, Quality Control, ML.

1. Introduction
Ready-made garment (RMG) is a structured industry that deals with the production of clothes, mostly in the form of export. It entails mass manufacturing of the finished apparel of refined textiles and is crucial in the overall manufacturing and growth of the economy of the country. By 2025, the world garment market will have an approximation1.84 trillion dollars. It is predicted to rise at a compound annual growth rate (CAGR) of 2.81% from 2025 to 2028 ig. 1) (Cardona, 2025). The RMG industry is very important for employment, foreign exchange revenues, and women's empowerment in underdeveloped nations such as Bangladesh. The RMG industry constitutes

approximately 11.2% of the country's gross domestic product (GDP) (Islam & Halim, 2022). It is an important part of the economy, but the industry continues to face several problems. Some of these challenges are reliance on manual labour, inconsistent product quality and low output efficiency. The combination of the elements of Industry 4.0 technologies and the use of the traditional manufacturing process can be used to address these challenges (Ben Ruben et al., 2023).

The demand for rapid delivery, improved efficiency via automation, superior quality, and customised products is propelling industries towards the Fourth Industrial Revolution, known as Industry 4.0 (Zheng et al., 2021). The adoption of advanced technologies has reshaped the modern industries as per Industry 4.0. Cyber-Physical Systems (CPS) refer to a set of breakthrough technologies that combine physical assets. The basic purpose of CPS is to monitor physical systems while making a digital copy of them. This enables systems to manage, automate, and synchronize in real time between the digital and physical spaces (Alguliyev et al., 2018). The IoT is likewise a network comprised of physical assets that are connected and share data with each other. These include devices, sensors, machines, cars, and buildings (Danner et al., 2024a). This connectivity allows intelligent devices to communicate, cooperate, and make decisions on their own, which maximizes performance efficiency. The role of Big Data and Analytics is no less important, as it involves the accumulation and analysis of large data sets with high speed, diversity, and volume. The approach can give valuable information to predictive maintenance, process enhancement, and decision making based on data (Buhl et al., 2013).

Cloud Technology also increases the industry's flexibility by providing a scalable platform for the storage and processing of applications and data online without local setups (Tao et al., 2011). Industrial robots and automation enhance high productivity and minimize quality concerns by undertaking either simple or difficult tasks on their own. Collaborative robotics facilitates secure and productive collaboration between people and machines in shared spaces (Cherubini et al., 2016). Lastly, Artificial Intelligence (AI) is an important component that enables systems to think and act smartly through machine learning, computer vision, natural language processing, and automated reasoning. Several smart automation, predictive analytics, and intelligent decision-making functionalities can be enabled in industrial processes via AI-driven solutions (Monostori, 2003).

ML is a specific branch of AI that enables computers to analyze data, identify patterns of information, and provide output conclusions or forecasts without being programmed. Unlike static instructions, ML algorithms become increasingly accurate with experience. Machine learning, as one of the major pillars of the Fourth Industrial Revolution (Industry 4.0), is facilitating automation, efficient and smart decision-making, and innovation in many industries worldwide (Sarker, 2021). Although an increasing number of companies are using Industry 4.0 technologies, machine learning is still not widely used in RMG manufacturing. ML technologies have grown and become more powerful in many different areas. ML is a type of artificial intelligence and computational approach that is used to find, obtain, and improve data-driven performance. It functions as a prediction model. That is, ML makes predictions based on what it has done previously on how it already performs and how it will perform better in the future (Lee et al., 2022). The garment industry is a good application for ML, as it helps in production planning, quality control, supply chain management, and predictive maintenance. Thus, in this paper, we provide a systematic review of the literature on machine learning applications in RMG manufacturing. Several recent studies have shown how ML technologies are changing the way different problems in RMG manufacturing are addressed.

In this context, the present paper attempts to offer a holistic review of the application of ML in different processes associated with RMG manufacturing for its transformation into Industry 4.0. The paper explains the application of the MLmethod in maximizing the productivity, quality and decision making at the different levels of production like during the procurement of raw materials, fabric checking process, post packaging and feedback during retail. This study also organizes current research based on the efficacy of machine learning in various processes and examines which algorithms work best. Then it analyses those algorithms 0 to understand the circumstances under which they can be applied successfully in real industry. This study also categorizes current works in terms of process-wise ML integration, identifies trends among the most frequently employed methods, and evaluates their functionality, except for refineries. Finally, it discusses the research gaps, new trends, and future directions that can support the garment industry in keeping pace with the digital era. The remainder of this paper is organized as follows: Section 2 presents the methodology used for the systematic review. Section 3 introduces the conceptual framework. Section 4 provides a detailed analysis of how ML is applied across different production processes, from raw material procurement to retail feedback. Section 5 discusses the challenges and limitations of ML adoption in the industry. Section 6 highlights future research directions and prospects, while Section 7 concludes the study with key findings and implications of ML-based Industry 4.0 adoption for the garment sector (Figure 1).

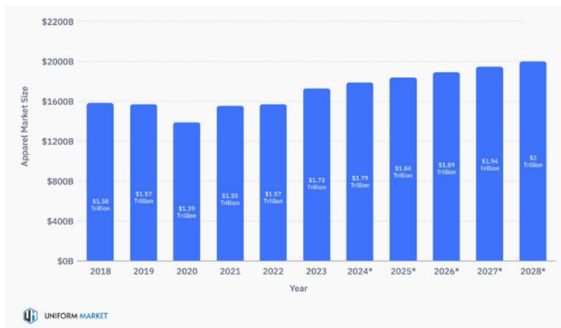

Figure 1. Global Apparel Market Size from 2018 to 2028 (in Trillions USD)

2. Methodology

This paper applies a systematic review approach to analyse the applications of MLin RMG industry with special emphasis on boosting up Industry 4.0 adoption. The methodology intends to provide a comprehensive, unbiased and reproducible literature coverage of relevant publications using the established systematic review drafting standards.

2.1 Literature Search Strategy

A structured search of key academic databases including Scopus, ScienceDirect, IEEE Xplore, SpringerLink and Google Scholar was conducted in papers from 2010 to 2025. Search terms included "machine learning" OR "artificial intelligence" OR "deep-learning" AND “garment manufacturing” OR “apparel industry” OR “RMG” AND “Industry 4.0” Or “smart factory” Or “automation.” Additional studies were identified by reference chaining and citation checks of key papers. Only peer-reviewed journal articles, conference papers and book chapters were included.

2.2 Inclusion and Exclusion Criteria

Inclusion Criteria: Studies in which machine learning or artificial intelligence-based is applied to garment or textile processing. Studies on production, quality control, inventory management and supply chain of RMG industries. English-language publications with full texts.

Exclusion criteria: Research focused only on dye and printing chemistry or fibre composition (not process automation). Papers in which the ML approach or performance measure is not clear. Repititive studies, theses, reports and non-peer-reviewed sources.

3. Conceptual Framework

The conceptual framework of this study illustrates the relationship between Industry 4.0 enabling technologies and their machine learning (ML)-driven applications within the RMG manufacturing process. It gives a clear picture of how ML works with different I4.0 parts, like the Internet of Things (IoT), Cyber-Physical Systems (CPS), Big Data Analytics, Cloud Computing, and Artificial Intelligence, to make production more efficient, improve quality control, and better manage the supply chain in the RMG industry (Table 1).

Table 1. Summary of Machine Learning Technologies and Applications Across Garment Manufacturing Processes

Process	**Machine Learning Application**	**References**
Raw Material Collection	Demand forecasting, inventory optimization, price prediction	(Douaioui et al., 2024a),(Deepa et al., 2023a),(Seyedan & Mafakheri, 2020a)
Fabric Inspection & Testing	Automated defect detection (CNNs), image analysis	(Wu et al., 2021a),(LeCun et al., 2015),(Hassan et al., 2024)
Fabric Relaxation & Spreading	Process optimization, tension prediction, quality assurance	(Vilumsone-Nemes, 2015a)
Pattern Making & Grading	Automated pattern recognition, fit & size clustering, CAD	(Datta & Seal, 2018a),(Han, 2025a)
Cutting Process	Vision-based defect detection, predictive cutting, nesting	(Hasan et al., 2021),(Lindström et al., 2023a)
Printing & Embroidery	Quality control, misprint/error detection, generative models (GANs)	(Datta & Seal, 2018a)
Sewing & Stitching	Defect detection, production optimization, robotic sewing	(Jung et al., 2025),(Ngan et al., 2011)
Finishing Operations	Automated defect recognition, process optimization	(Zhang, 2025)
Final Inspection & Quality Control	Deep learning for fault detection, predictive analytics	(Yosephine et al., 2024a)
Packaging & Shipment	Packing optimization, defect detection, packing prediction	(Heininger & Ortner, 2022)
Delivery & Retail Feedback	Forecasting, sentiment analysis, logistics, trend prediction	(Faridi et al., 2023)

4. Analysis of RMG Manufacturing with Machine Learning Integration
This chapter presents a detailed analysis of the key processes involved in RMG manufacturing. It highlights how modern technologies, particularly machine learning and Industry 4.0 innovations, are transforming each stage from raw material collection to delivery and retail feedback.

4.1 Raw Material Collection
To make clothes, the first thing we have to do is collect raw materials. Cotton, polyester, and denim are some of the key materials that go into these fabrics. Buttons, zippers, threads, labels, hang tags, and packing materials are entirely made of polyester, examples of accessories. The material is sourced from local textile mills or imported from China, India, and Pakistan. Current garment businesses are increasingly relying on machine learning to ease the process of obtaining raw materials faster and more accurately.

Predictive Analytics models analyse historical sales data, effects of seasonals, and marketing trends record in an accurate way the fabric demand and raw material needs (Douaioui et al., 2024b). For demand prediction, we have learned the use of models such as random forest, gradient boosting, and XGBoost, of which the latter was found most suitable due to greater accuracy for prediction (Ji et al., 2019).

Supplier Selection Models use computational logic provided by algorithms like Random Forest, Support Vector Machine (SVM), to consider delivery lead time, defect rate, and other elements of reliability into decision making in selecting suppliers as extracted from the data (Wang et al., 2020).

ML-driven regressions predict future fabric prices in view of the IoT data, world indices, and demand fluctuation for constant valuing, resulting on minimal overall procurement planning (Deepa et al., 2023b). Raw-materials procurement can be improved by better demand forecasting and inventory management made possible by machine learning. Data analysis and market trends enable machine learning algorithms to predict raw material needs (Table 2).

Table 2**.** Overview of AI/ML Techniques in Supply Chain Demand Forecasting

ML/DL Models Used	Dataset Characteristics	Key Findings	Advantages	References
Various ML models (Random Forest, SVM, Neural Networks)	Large-scale retail dataset with diverse product categories	AI/ML models significantly outperform traditional forecasting methods	Improved accuracy and adaptability	(Seyedan & Mafakheri, 2020b)
Hybrid models combining regression and neural networks	Industrial production and sales data	Hybrid models reduce forecasting errors up to 20% compared to standard methods	Effective in capturing complex patterns	(Chien et al., 2020)
Deep learning models (CNN, LSTM)	Supply chain operations data	DL models enhance demand prediction accuracy, especially for volatile demand patterns	Handles large datasets effectively	(Aamer et al., 2020)
Gradient Boosting, Decision Trees	Manufacturing and logistics datasets	AI-driven models increase efficiency in supply chain management by optimizing inventory levels	Reduces human intervention in forecasting	(Sardar et al., 2021)

4.2 Fabric Inspection and Testing

Human eye inspection is a common method in the fabric industry (Wu et al., 2021b). Visual inspection can detect flaws as well as classify them. The human detection is only 12 meters per minute. However, the irregular operation frequency of the job can cause waste of human resources and cost money, so it is not good for large-scale manufacturing. And while it is easy for people to point out flaws, laborers struggle because production lines and products are so complex. With these challenges in manual inspection, the industry is gradually shifting towards automation solutions, claiming to be more precise and time-efficient for stomata detection. It is necessary to replace the present manual labor with a new method of reading detection, which can be fast and accurate. Spurred by the rise of CNNs (convolutional neural networks), deep learning, and machine vision (Lecun et al., 2015). These advancements in recent years have, in turn, given rise to an increasing many detection methods that combine their strengths, making traditional image processing and manual methods outdated.

4.3 Fabric Relaxation and Spreading

Fabric relaxation refers to the process whereby continual straining of a fabric results in a progressive decrease of tension. The long-time relaxation predictions are influenced by the study's finding of a breakpoint at 100 sec, where the relaxation rate scale changes (Milašius & Laureckiene, 2014). It is important to understand fabric relaxation just before the spreading process, because it guarantees that the material is spread precisely and has no residual tension that can disturb the cutting precision. The process of spreading cloth entails laying more than one layer of fabric in a flat position on a table prior to cutting. The primary goal is to eliminate the inaccuracies of tension-free material laying. Spreading can be done either by hand or by an automatic spreading machine. The spreading method, such as Face Up, Single Direction, and Zig-Zag, is influenced by the fabric type (Vilumsone-Nemes, 2015b).

4.4 Pattern Making and Grading

Pattern making and grading are classical stages of clothing manufacturing, which used to be conducted manually by drawing, which is time-consuming and prone to mistakes (Datta & Seal, 2018b). However, the industrial 4.0 technologies, and ML in particular, encompassed in computer-aided design (CAD) systems, have made these processes faster, more precise, and data-driven (Han, 2025b). Pattern making Computer-aided pattern making (CAPM) is now used to create patterns based on body measurements, 3D scans, or style input, with the aid of ML tools enhancing automation and accuracy (Pietroni et al., 2022). Some sophisticated algorithms like Generative Adversarial Networks (GANs) and neural networks can be used to generate new patterns out of existing databases to satisfy a particular design or fit need (Danner et al., 2024b). Regression-based systems and AI-facilitated CAD systems improve the prediction of the fit by analysing body size data, and identify pattern errors and asymmetries prior to the cut, minimizing errors in the production (Pietroni et al., 2022). In general, the ML applications have a massive effect on the speed of the development of patterns, their consistency, and accuracy. The art of grading, or the scaling of various garment sizes, has also been updated to include ML-based CAD systems such as Gerber AccuMark, Lectra Modaris and Optitex which are more efficient and reliable than manual scaling (Xiu & Wan, 2011). The ML algorithms forecast the size distribution basing on the customer demand, sales trends, regional anthropometric information, and allow a more optimized planning of sizes (Han, 2025c). Virtual try-on systems and returned garments inputs additionally enhance the rules of grading and can be automatically modified to enhance fit in the subsequent production cycles (Danner et al., 2024c). Moreover, clustering methods classify body shapes and grading interventions to be more realistic of anthropometric variation. All these innovations increase productivity, minimize mistakes, and contribute to data-driven decision-making in the work of the modern RMG.

4.5 Cutting Process

RMG production entails cutting the layers of fabric into garment parts as per the readymade pattern shapes. Conventional systems, including straight-knife and band-knife cutters, round-knife cutters, and CNC units, are meant to ensure consistency and minimize resource wastage since the accuracy of cutting has a direct influence on the fit of the garments, the placement of the seams, and the use of fabrics (Hasan et al., 2021). Nevertheless, these problems are commonly present in the cutting process as it typically lacks accurate fabric alignment, operator reliance, variable quality, and unproductive marker layout. The manual or semi-automatic cutting process also creates an increase in material waste and time spent in the cycles, particularly issues in mass customization and just-in-time settings (Rahman & Rashid, 2017). Machine learning is presenting game-changing advances in the cutting stage with intelligent data-driven solutions. Computer vision systems that are based on MLs are capable of evaluating properties of fabrics in real time, anticipating deformation and automatically refining cutting paths to increase accuracy and reduce waste.Furthermore, predictive analytics can optimize cutting layouts and equipment-maintenance schedules, promoting sustainability and cost efficiency within Industry 4.0-driven RMG operations (Lindström et al., 2023b).

4.6 Printing and Embroidery

Print designs on garments, especially on knitted T-shirts and Polo shirts, are very common (Figure 2). Prints on ladies dresses and Kurtis, which are primarily all-over prints, are done at the fabric stage. Printing is a value addition process and printed designs are a trend in all types of garments. I will describe different techniques of garment printing, used to print designs on garments or garment panels. Printing is categorized based on printing techniques. Embroidery is a value-added process in garment manufacturing. Embroidery can be done on garment panels after cutting or at the fabric stage. There are various ways to get embroidery work done. Inconsistent print quality, colour variations, skipped stitches, misalignment, high labour dependency, and labour-intensive human inspection—which frequently results in inefficiency and defects—are among the difficulties these systems have historically faced. These problems can be effectively solved by machine learning (ML): computer vision models, such as convolutional neural networks (CNNs), can detect misprints, colour deviations, or embroidery errors in real time; predictive models optimise workflow scheduling and machine parameters; generative models, such as GANs, enable automated pattern generation for mass customisation; and ML-based quality prediction allows preventive interventions by analysing machine settings, operator performance, and environmental conditions (Hassan et al., 2024),(Jerusha & Kumar, 2025),(Vijaya Bhaskar.Reddypogu, Devi Prasad.U, 2025).

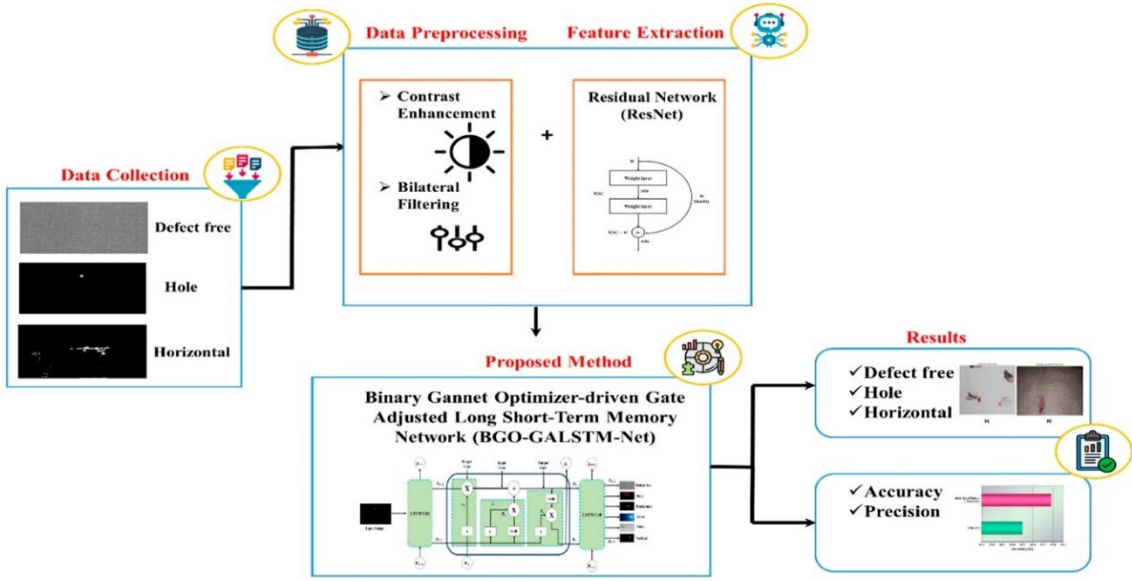

Figure 2. Automated Textile Defect Detection Workflow Using BGO-GALSTM-Net.

4.7 Sewing / Stitching

Sewing/stitching process is considered as one of the important stages in Ready-Made Garment manufacturing where parts are assembled further to make a complete garment. Historically, this process was highly labour-intensive, with skilled operators sewing on sewing machines. However, due to the flexibility of human operators, quality control of manual hand sewing tends to be compromised and its practical use is restricted in the cycle time and cost per man. Human error, such as jacket pocketing pockets with uneven stitches and skipped seams resulting from tension problems, is also expensive because of ruined garment and increased re-work percentages (Jung et al., 2025). To address these limitations, nowadays textiles and garments production factories have also updated their operations with Industry 4.0 techniques using machine learning and computer vision for fully automation and optimization of the stitching process (Ngan et al., 2011). Robot Sewing Systems are designed to automate monotonous stitch tasks in an accurate and repeatable manner. Such instruments are further provided with sensors and cameras that define the needle path and regulate stitch quality in real-time(Gries & Lutz, 2018). Defect detection is an important application of ML in sewing operations. Computer vision models, particularly convolutional neural networks (CNNs), are trained on massive datasets of stitched fabrics to detect flaws including skipped stitches, puckering, thread breakage, and misalignment (A.Raghuvardhan Babu, 2025). These models recognize defects early enough that action can be taken in real time to produce less waste and increase product quality. Another crucial point for the application of machine learning on sewing is production efficacy. It can be utilized for algorithms to identify bottlenecks and corrective workflow using historical production data, operator efficiency, machine performance and line balancing (Ersöz et al., 2021). In summary, incorporating machine learning, computer vision, and robotics into sewing and stitching operations improves seam consistency, decreases errors, increases production throughput, and eliminates labor dependency. These developments have a substantial impact on current RMG manufacturers' operating efficiency, quality control, and compliance with Industry 4.0 concepts.

4.8 Finishing Operations

The finishing section is responsible for achieving the final appearance with the correct quality and handle for clean or unclean clothes. While in this step, clothes pass through many steps to have buttons fixed, threads cut, ironed and packed. These operations are performed in a sequential and linear order to have an even work-flow and uniform production flow (La & Kddn, n.d.). Conventionally, such processes were labor intensive need workshop style workmanship which is quite inefficient as a result of inconsistent product quality increasing labour cost and low operating efficiency. In order to eliminate these limitations, finishing departments are employing Industry 4.0 technologies such as ML and computer vision systems in order to automate repetitive tasks and enhance the overall production to meet market demands. For instance, in the area of the visual inspection, ML-based defect detection systems leverage image processing and DL algorithms like CNNs to identify common finishing faults such as uncut threads, loose buttons, incorrect folding, or errors in tagging rapidly and accurately. The presented system is trained and tested on a state-of-the-art dataset, which involves various defect types including stains, holes, and misweaves. The data preprocessing integrates the image contrast-enhanced and edge-preserving smoothing, enhancing the defect visibility, while the feature extraction relies on a residual network (ResNet) to enable focusing on the complex affected areas. We have presented a novel BGO-GALSTM-Net which exploits LSTM memory capability to keep temporal records, and adaptive gating to exploit the Binary Gannet Optimizer that is adopted for tuning network's parameters for better performance (Zhang, 2025).

4.9 Final Inspection and Quality Control

The last phase of inspection and quality control during the garment production process is important in ensuring that the buyer's requirement is met before the delivery. Conventionally, it is based on the manual examination of the workers who visually examine any defects. But human inspections may be subjective, slow, and influenced by external environmental factors, which results in low correlation to the product quality (Hoque & Maalouf, 2022). Machine learning technologies are currently being applied in order to automate this process to overcome these challenges. Computer vision and convolutional neural networks (CNNs) are the techniques that can detect faults in real-time with high precision, which is between 75-100 (Yosephine et al., 2024b). Moreover, the defect probabilities can be predicted using predictive quality models, which rely on the information of production machines and operators and can be used to take proactive steps prior to being detected. It is an automated method that minimizes human error, offers digital records and quality assurance, leading to more dependable products, decreased rejection rates and customer satisfaction (Ozek et al., 2025).

4.10 Packaging and Shipment

During the packaging and shipment stage, finished garments are folded, tagged, bagged, grouped into cartons, labelled, palletized, and loaded for transport while order traceability and export documents are maintained. When such processes are manually driven by discretion and rule-of-thumb heuristics, frequent examples of suboptimization include over- or under use of material (and waste or damage), mislabelling or picking errors, lack of compression in load and unnecessary empty space on pallets/containers, and routing/scheduling inflexible to react to real-life disruptions - all involving cost increase, waste generation and inability to deliver correctly. This stage can be turned into a data-driven, adaptive procedure via machine learning. Supervised models, using training set from past orders/dimensions and damage outcomes, can recommend what will the best carton/polybag of different sizes and folding two packing to maximize the use of material and less time for packing (Heininger & Ortner, 2022). Deep-learning computer-vision systems (YOLO/Faster-R-CNN versions) can inspect packed units in real time to discover sealing defects, lost tags, or visual damage before shipment (Liu et al., 2025). Deep reinforcement-learning or hybrid DRL heuristic algorithms can develop near-optimal 3D bin, pallet, or container packing layouts that maximize space utilization and reduce handling damage (Murdivien & Um, 2023),(Wong et al., 2024).

4.11 Delivery and Retail Feedback

The delivery and retail feedback stage is the last stage of the RMG production process, in which produced garments are sent to buyers, distribution centers, or retail outlets from where purchased and consumed by ultimate customers. In any case, for the delivery on time, and to keep production connected with the market demand by maintaining the product quality, a fast feedback cycle and efficient logistics are critical. Real-time shipment tracking technologies, including such as RFID and IoT sensors, enable visibility into shipment location, transit conditions (e.g., temperature, humidity), and estimated time of arrival, as a result, reducing shipping errors and enhancing logistics planning (Anca & Andreea, n.d.).

To guarantee product authenticity and traceability from point-of-origin to the end consumer, blockchain with IoT has been suggested as an authentic system for apparel supply chains. Transparency in recording production, movement, and ownership events for each garment or batch is made possible by blockchain smart contracts and immutable ledgers, powering recall management, anti-counterfeit measures, and auditability among stakeholders. AI-based frameworks for fashion demonstrate how RFID/IoT data can be anchored to a blockchain to produce authentication provenance records (Faridi et al., 2023). Capturing retail sentiments collected from point-of-sale systems, e-commerce reviews, returns data, and social media, they are increasingly processed using machine learning (ML). Demand-forecasting models that include historical sales, product attributes (including image features), promotional calendars, and external signals (e.g. weather, events, social trends) can reduce inventory mismatch and stockouts significantly. Deep learning and ensemble ML approaches have led to better forecasting accuracy for fashion products, leading to improved production planning, ultimately reducing waste (Swaminathan & Venkitasubramony, 2024). Sentiment analysis and aspect-based sentiment analysis (ABSA) are used to find useful information about fit, quality, color, and other features in customer reviews and text feedback. These NLP methods let manufacturers decide which corrective actions to take first (like changing the grade, changing the material choice, or changing the packaging) and then use that information to improve future batches by feeding it back into the design and production cycles. Several recent studies show that ABSA and sentiment models work very well on clothing reviews from online stores. In the Bangladesh RMG industries, pilot use cases of IoT/RFID for Work-In-Process (WIP) tracking and smart logistics have yielded tangible benefits in shop-floor monitoring and shipment traceability, proving that such technologies can be scaled within export-oriented factories. Integrating these tools into centralized dashboards enables Key Performance Indicator (KPI) tracking (lead time, on-time delivery, return rates, and customer satisfaction indexes) to act as insight for data-driven inventory control, dynamic production schedules, and continuous improvement (Varriale et al., 2021).

5. Challenges and Limitations

Although ML and Industry 4.0 have been adopted in the RMG industry, the problem of low data availability and quality, privacy, technical heterogeneity, skill gap, cost, and regulation challenges impede this process. The manufacturers do not always have homogenized digital infrastructures, which results in disintegrated datasets that decrease the accuracy of ML models. Moreover, the presence of legacy equipment makes it hard to integrate with new ones, and to successfully manage the data, employees need to be trained. SMEs are not able to invest in modern technologies due to financial constraints. The problems of generalizing models and ethical issues concerning automation also contribute to the complexity of the shift to Industry 4.0 in garment production.

6. Future Prospects and Research Directions

An intelligent system developed with the use of ML-driven Industry 4.0 in RMG manufacturing is aimed at improving the quality of decision-making and innovation through technologies such as Large Language Models (LLMs), digital twins, and edge computing. The processes can be automated with the use of an LLM that processes the unstructured data to create actionable insights and enables the machine and operator to communicate in real-time. The research in the future must focus more on hybrid intelligence applications that combine ML, LLM, and reinforcement learning to optimize processes, and use blockchain and IoT to enhance transparency in the supply chain. Sustainability is an essential factor, and digital twins will contribute to energy efficiency and waste management. Open datasets and IoT solutions based on developing countries require collaboration to be developed. Overall, combining these technologies will contribute to the development of autonomous and sustainable garment production systems that comply with the ethical manufacturing standards.

7. Conclusions

This literature review highlights the disruptive nature of ML in the RMG sector in the I4.0 framework. ML integration can improve productivity, consistency, and competitiveness across production processes, making the detection of defects, resource management, and predictive maintenance possible. Nonetheless, issues, including the unavailability of standardized datasets, incompatibility, the deficiency of the digital infrastructure, and high initial investment rates, make the adoption problematic. Digital transformation requires workforce readiness and upskilling because it is important that human skills and AI collaborate in equilibrium. The fusion of ML with Large Language Models (LLM), Digital Twins, Edge Computing, and Explainable AI (XAI) will further the idea of intelligent insights and self-optimizing production environments in the future. Regarding sustainability, ML promotes energy consumption, material waste and is compatible with the Sustainable Development Goals (SDGs) of the United Nations, with eco-efficient opportunities and the circular economy. In countries such as Bangladesh, using ML and Industry 4.0 may result in a higher global competitiveness and supply chain resilience. Academic-industrial partnerships and policy play a crucial role in developing digital infrastructures and training of the workforce. Altogether, the combination of ML and Industry 4.0 indicates the transition to the intelligent and sustainable manufacturing process.

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