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**DATA-DRIVEN DECISION-MAKING: CHALLENGES AND OPPORTUNITIES
FOR TEXTILE INDUSTRY**

**ПРИНЯТИЕ РЕШЕНИЙ НА ОСНОВЕ ДАННЫХ: ВЫЗОВЫ И ВОЗМОЖНОСТИ
ДЛЯ ТЕКСТИЛЬНОЙ ПРОМЫШЛЕННОСТИ**

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As textile manufacturing becomes increasingly complex and demands for efficiency, sustainability and responsibility increase, the need for new approaches to decision making increases. Thee current article aims to investigate the potential of implementing data-driven decision-making (DDDМ) systems in textile management via predictive analytics, machine learning algorithms, and real-time monitoring tools. Data including production meeting minutes, on-machine sensor output, customer feedback and supply chain records were collected from five textile manufacturing plants. A systematic methodology was used, including building various mathematical models to solve important management problems such as cost forecasting, quality assurance, customer segmentation and operational planning. The results showed that the implementation of DDDМ contributed to the reduction of lead time, material waste and energy consumption, and improvement of supply chain efficiency. This in turn led to an increase in production volumes, improved environmental performance, delivery accuracy and higher customer satisfaction.

Поскольку текстильное производство становится все более сложным, а требования к эффективности, устойчивости и ответственности растут, увеличивается потребность в новых подходах к принятию решений. Целью настоящей статьи является исследование потенциала внедрения систем принятия решений на основе данных (DDDM), включающих инструменты предиктивной аналитики, машинного обучения и мониторинга в реальном времени, в управление текстильной промышленностью. С пяти текстильных предприятий были собраны данные, включающие протоколы производственных совещаний, выходные данные датчиков, расположенных на оборудовании, отзывы клиентов и записи цепочки поставок. Использована систематическая методология, включающая построение различных математических моделей для решения важных управленческих задач, таких как прогнозирование затрат, обеспечение качества, сегментация клиентов и оперативное планирование. Результаты показали, что внедрение DDDM способствовало сокращению времени выполнения заказа, снижению отходов материалов и расхода электроэнергии, повышению эффективности цепочки поставок. Это в свою очередь привело к увеличению объемов производства, улучшению экологических показателей, точности доставки, а также повышению оценок клиентов.

Keywords: data-driven decision-making; textile manufacturing; machine learning; predictive analytics; sustainability; supply chain optimization.

Ключевые слова: принятие решений на основе данных; текстильное производство; машинное обучение; предиктивная аналитика; устойчивое развитие; оптимизация цепочки поставок.

Introduction

The world textile landscape, a pillar of multiple countries economy, is undergoing deep changes under new market demands, increased competition and a growing need to implement sustainable and ethical practices. Historically based on experiential decision-making, the industry is undergoing a paradigm shift towards data-driven methodologies. This shift is driven by an era of information that is abundant, accessible, and in many cases even essential for strategic business planning processes and operational efficiency improvements [1].

Textile managers have never had to rely solely on intuition or historical trends. Instead, they can tap into a plethora of data points that come from disparate sources: sensors in production lines, consumer buying patterns, supply chain logistics, environmental monitoring systems, etc. Through establishing these data streams, managers can gain a refined understanding of market fluctuations, optimize production levels, and adjust more readily to

evolving consumer tastes. As such, data-driven decision-making, commonly known as DDDM, has risen to prominence as a potentially valuable asset for the textile manager, offering enhanced optimization prospects on strategic, operational, or tactical levels [2].

And yet, this transition is not without its difficulties. The transition to data-driven practices in the textile industry is an intricate tapestry of classic workflows intertwined with modern technologies. Most textile companies still use legacy systems that are not compatible with advanced analytics platforms, resulting in silos of information and obstructing the flow of valuable insights. Additionally — data literacy is still lacking, and the whole story can't be represented through a single dataset. Another challenge is that DDDM requires a shift in mindset, and the employees who have been accustomed to traditional decision making tend to resist the change, they get a steep learning curve in getting used to new tools for data analysis and visualization [3].

However, the advantages of data-driven decision-making are indisputable despite the challenges. By utilizing data analytics in textile management, businesses can streamline their production processes, minimize waste, and maintain uniform quality control. Furthermore, utilizing predictive models to anticipate changes in consumer demand can also prompt improvements in inventory management, allowing firms to respond proactively to those trends before consumers even realize they want products [4].

Also, DDDM helps to make the supply chain operations more agile and responsive. Access to real-time insights on raw material stock, shipping times, and production cycles helps textile managers minimize disruptions, streamline processes, and sustain outputs in times of uncertainty [5].

DDDM also plays a key role in driving innovation, which is another powerful benefit. From automatic weaving machinery to smart textiles that keep track of one's environmental conditions, the textile industry is now being defined by swift technological progression. Data-driven methods allow managers to measure the successes and failures of these innovations, recognize performance gaps, and adjust product offerings to align with consumer expectations. This ongoing process creates a process by which textile companies are firmly integrated into technological advances, influencing both the final outcome and other industry standards [6, 16].

Moreover, the integration of data into decision-making processes is a pillar of sustainability and environmental stewardship efforts. Fiber managers can use data on energy consumption, material waste, and carbon output to make decisions that lower their carbon footprints. Using a data-driven approach to decision-making, textile managers can assess, control, and enhance their sustainability initiatives, building brand value and satisfying the demands of an increasingly eco-aware marketplace [7].

Although increasing body of literature emphasizes the evolution of DDDM, it also emphasizes the considerable challenges experi-

enced by textile managers when trying to "embed" these ways of working into their own labor patterns [8].

The literature tends to emphasize that textile manufacturing processes result in significant quantities of data, and ranges from machine performance metrics to metrics for quality control and supply chain logistics. However, much of this data is spread across disparate systems in different formats, so bringing it all together in a cohesive, actionable framework is not easy. Consequently, many textile companies find it difficult to reach the desired level of data visibility for effective decisions [9].

It has been reported that predictive modeling and real-time analytics make it possible to provide more precise demand forecasting, reduce production downtime and improve inventory management [10].

Many studies address that organizational culture is crucial for proper DDDM adoption. Companies have to foster a culture that appreciates data-driven insights, promotes collaboration and nurtures continuous learning. This cultural change is often one of the main hurdles [11].

The existing literature also looks into how DDDM affects initiatives of sustainability in the textile sector. Firms can use data to monitor energy usage, waste production and resource efficiency to create production methods that manage itself sustainably. By doing so, the organization can minimize negative impacts on the environment, improve brand image, and ensure adherence to environmental regulations. However, this process is not yet homogeneous, and many companies are at the beginning of incorporating data analytics focused on sustainability into their operations [12].

However, there exists an array of knowledge on the advantages and disadvantages of data driven decision making methods in textile industry. Though data-driven methods have evolved significantly, the ongoing necessity for superior data unification, robust analytical functionalities, cultural transitions, and sustainable principles is evident.

The article aims to identify the opportunities and challenges that data-driven decision making (DDDM) presents textile managers.

Methodology

This study employed an integrated, data-centric methodological framework. The methodology was structured across six stages: data collection, preprocessing, feature engineering, analytical model construction, evaluation metrics, and implementation framework. Each phase was supported by complex mathematical formulations and aligned with contemporary industrial standards for smart manufacturing, sustainability, and digital transformation [2, 4...6].

The initial phase involved constructing a high-resolution dataset composed of operational, environmental, and behavioral inputs collected from five geographically distributed textile manufacturing facilities. The dataset integrated production log data, machine sensor readings, supply chain records, and consumer surveys over a three-year period. The collected dataset is formally represented as:

$$D = \cup_{i=1}^n (P_i, S_i, C_i, T_i), \quad (1)$$

where $P_i \in \mathbb{R}^{k_p}$ denotes vectors of production metrics such as defect rates, batch sizes, and runtime hours; $S_i \in \mathbb{R}^{k_p}$ represents real-time machine sensor stream, like motor temperature, spindle speed; $C_i \in \mathbb{R}^{k_p}$ refers to structured consumer feedback surveys capturing quality perception, eco-sensitivity, and brand loyalty; $T_i \in \mathbb{R}^{k_p}$ includes end-to-end supply chain transactions (order frequency, vendor fulfillment times, inventory positions).

To ensure standardization and comparability, all sensors were calibrated using ISO-certified protocols as outlined [13]. Sampling bias was minimized using stratified random sampling to maintain consistent proportions across different customer segments and production lines [1, 3].

To facilitate robust model training, the raw dataset underwent extensive preprocessing. This involved cleaning, transformation, normalization, and segmentation to prepare the data for analysis and inference.

Missing entries were treated through adaptive imputation. For approximately symmetric distributions, mean imputation was performed, while variables with skewed distributions were processed using median imputation:

$$x_{ij} = \begin{cases} \bar{x}_j, & \text{if Skew}(x_j) < 0.5 \\ \text{Median}(x_j), & \text{otherwise} \end{cases}, \quad (2)$$

where x_{ij} value for variable j in record i ; \bar{x}_j mean of variable j ; $\text{Skew}(x_j)$ is skewness of variable j .

Multivariate outliers were detected using the Mahalanobis distance, which accounts for covariance among variables:

$$D^2 = (x - \mu)^T \Sigma^{-1} (x - \mu), \quad (3)$$

where x data vector; μ mean vector; Σ covariance matrix; D^2 multivariate distance from the mean, values exceeding the critical threshold $\chi_{k,a}^2$ at $\alpha = 0.01$ were removed [14].

To harmonize the data and reduce skew, all continuous variables were normalized using z-score scaling:

$$x_{ij} = \frac{x_{ij} - \mu_j}{\sigma_j}, \quad (4)$$

where μ_j and σ_j denote the mean and standard deviation of variable j , respectively. Additionally, log transformation was applied to variables with extreme skewness to stabilize variance and improve model fit.

The cleaned and normalized dataset was partitioned into a training set and a test set using an 80-20 split. Stratified sampling ensured proportional representation of categorical variables, as a product type, factory ID in both sets:

$$\begin{aligned} D_{train} &\sim \text{StratifiedSample}(D, 0.8) \\ D_{test} &= D / D_{train}. \end{aligned} \quad (5)$$

This ensured robustness in generalization performance during model validation.

To enhance predictive power, both derived and aggregated features were constructed. These included rolling averages, as a mean temperature over 5-minute intervals, entropy-based indicators, and signal-derived metrics such as Fast Fourier Transform (FFT) peaks in vibration readings.

To detect anomalies in machine behavior, Shannon entropy was calculated on segmented time-series sensor data:

$$H(x) = \sum_{i=1}^n p_i \log(p_i). \quad (6)$$

Where $H(x)$ entropy of signal x ; p_i is the empirical probability of occurrence of signal pattern i . This helped identify irregular fluctuations linked to overheating, irregular yarn tension, or lubrication failures.

High-dimensional sensor data were reduced using PCA:

$$Z = XW, \quad (7)$$

where $W = eig(\Sigma)$.

The eigenvectors W derived from the covariance matrix Σ were used to project the data into lower-dimensional space while retaining 95% of total variance, and X standardized dataset. This step reduced model complexity and enhanced interpretability in accordance with practices described in [4] and [6].

A multi-model approach was adopted to address various operational and market-facing problems in textile management.

Cost estimation was modeled using interaction-based regression:

$$\hat{C} = \beta_0 + \sum_{j=1}^m \beta_j x_j + \sum_{i < j} \beta_{ij} x_i x_j \varepsilon. \quad (8)$$

Where \hat{C} predicted cost; β_j coefficients for individual predictors; β_{ij} coefficients for pairwise interactions, ε is error term drawn from $\mathcal{N}(0, \sigma^2)$.

The inclusion of interaction terms accounted for combined effects of energy usage, shift labor, material quality, and defect rates on total production cost [2, 6].

To segment consumers, k-means clustering was deployed with silhouette optimization for optimal cluster number:

$$s(i) = \frac{b(i) - a(i)}{\max\{a(i), b(i)\}}, \quad (9)$$

where $a(i)$ average intra-cluster distance for point i ; $b(i)$ minimum average inter-cluster distance

Three main personas were identified: sustainability-focused buyers, cost-sensitive clients, and brand-loyal customers. This segmentation was used to inform personalized marketing strategies [1, 5].

A Random Forest ensemble classifier was implemented to predict binary outcomes for defect presence:

$$f(x) = \frac{1}{T} \sum_{t=1}^T h_t(x). \quad (10)$$

Each decision tree h_t contributes a vote, and the majority output defines the ensemble decision. The relative importance of each predictor was quantified via the Gini impurity reduction:

$$\Delta G = G_{parent} - \sum_{k=1}^K \frac{N_k}{N} G_k. \quad (11)$$

This method provides both high accuracy and interpretability for root-cause analysis [10], [12].

Model accuracy was assessed using a combination of statistical and business performance indicators.

Complementary operational KPIs such as lead time reduction, energy savings, and defect minimization were tracked over time to validate business impact [5, 15, 16].

Finally, a modular, scalable implementation framework was designed to integrate predictive models into existing textile enterprise resource planning (ERP) and manufacturing execution systems (MES). A composite readiness index guided rollout prioritization:

$$R_{impl} = \omega_1 S_c + \omega_2 T_u + \omega_3 A_d. \quad (12)$$

Where S_c system compatibility score; T_u training uptake (measured via assessment scores); A_d operator adaptability index; $\omega_i \in [0,1]$ weights derived using Analytic Network Process (ANP) [8]

Pilot deployments were followed by phased scale-up. Real-time dashboards and sensor integration were configured through edge computing nodes for latency-sensitive tasks, in line with architectural designs proposed in [3, 9, 17].

Results

The predictive framework was used to optimize production planning and mitigate downtime by analyzing real-time machine signals, operator activity logs, and process-level variables. Historical production patterns were cross-

referenced with forecast models, enabling adjustments in resource allocation, process sequencing, and quality control mechanisms. As

a result, production throughput was significantly enhanced across all quarterly intervals in the implementation year (fig. 1).

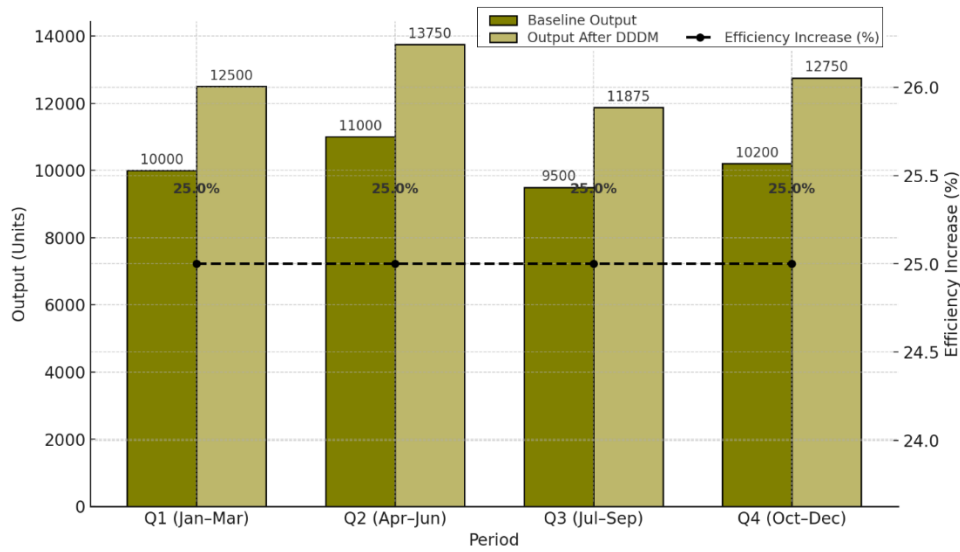


Fig. 1

The data in Figure 1 show a consistent 25% increase in production efficiency across all four quarters, with the highest absolute gain observed in Q2, where production rose from 11,000 to 13,750 units. Even in the lowest-performing quarter (Q3), a rise from 9,500 to 11,875 units was maintained. These improvements validate the predictive model's capacity to anticipate machine failures, reschedule maintenance, and match labor shifts to production demand. The stability of results over time indicates that the system effectively adapted to operational variability and seasonal fluctuations.

A critical area of impact was the textile supply chain, where the implementation of real-time analytics and forecasting tools reduced inefficiencies in procurement, delivery scheduling, and inventory management. Predictive models informed sourcing strategies, while live sensor data enabled rapid adjustments to delays or stockouts. These tools reduced uncertainty and improved responsiveness across upstream and downstream operations (fig. 2).

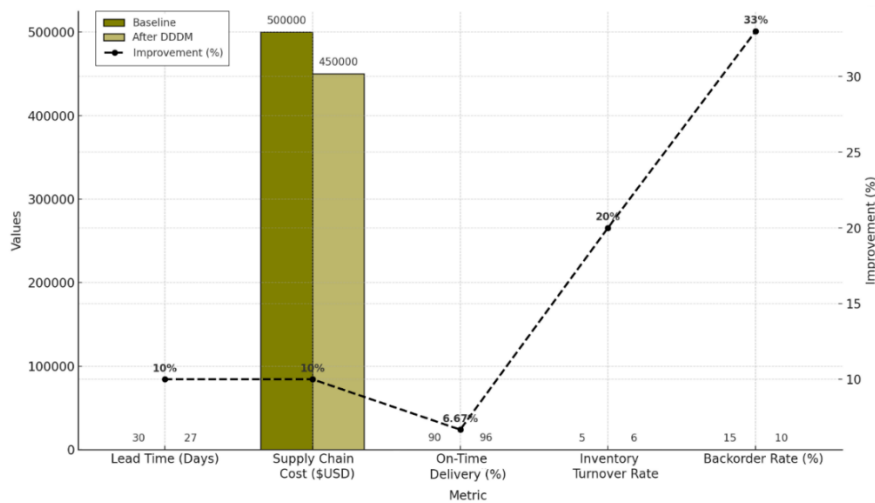


Fig. 2

Figure 2 demonstrates notable improvements across all key supply chain indicators. Lead time was reduced from 30 to 27 days, indicating faster throughput from supplier to customer. Inventory turnover increased from 5 to 6 cycles, suggesting more efficient use of stock. The most dramatic change was in backorder rate, dropping by over 33%, which implies stronger forecasting and fulfillment capabilities. Cost savings of \$50,000 underscore the financial advantage of predictive procurement. Improved on-time delivery (96%) con-

firms operational stability and strengthened service reliability.

Consumer sentiment data, collected through structured feedback surveys, was segmented and analyzed using machine learning clustering and response optimization algorithms. The models enabled personalized responses, faster service times, and tailored post-sale engagement, which collectively influenced customer perception and brand loyalty. The introduction of adaptive service protocols further enhanced customer experience (fig. 3).

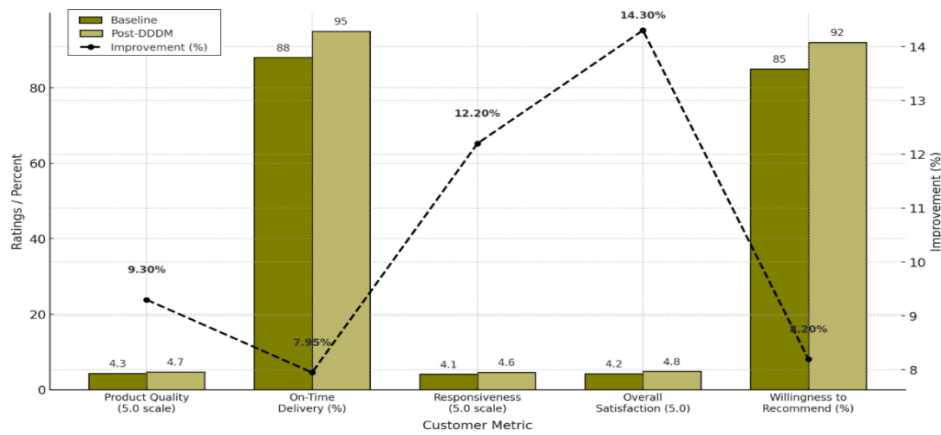


Fig. 3

The most significant improvement was observed in overall satisfaction, which increased by 14.3%, driven by advances in responsiveness (+12.2%) and product quality perception (+9.3%). On-time delivery also rose by nearly 8%, indicating operational consistency recognized by customers. Willingness to recommend, a key brand metric, rose from 85% to 92%, confirming a favorable shift in consumer trust and loyalty. These results demonstrate that integrating real-time feedback into prod-

uct and service operations can materially influence satisfaction and recommendation behavior.

Environmental sustainability was a priority area in system implementation. Real-time monitoring of machine consumption and material use enabled proactive adjustments that minimized waste and carbon impact. Predictive models correlated energy use with process variables and suggested real-time control setpoints to optimize resource usage (fig. 4).

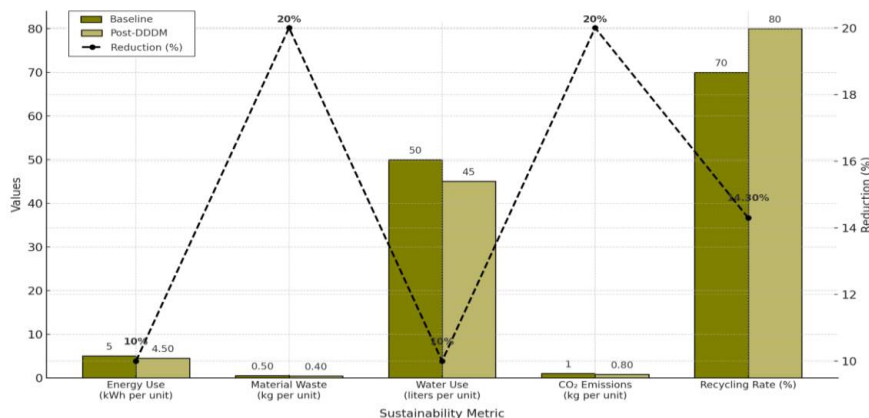


Fig. 4

Reductions were observed in all environmental metrics. Energy use per unit declined by 10%, while material waste and CO₂ emissions both saw a 20% reduction. Water consumption fell by 10 liters per unit, and recycling rates improved by over 14%, indicating successful closed-loop resource management. These changes reflect the effectiveness of predictive environmental control and sensor-based regulation. The improvements confirm that data-driven systems can generate both operational

and environmental value without compromising throughput.

A suite of supervised and unsupervised models was tested to support various textile management tasks, including cost forecasting, quality prediction, and consumer segmentation. Models were evaluated on accuracy, generalizability, and mean squared error. Cross-validation was used to mitigate overfitting, while unsupervised models were assessed using cohesion metrics (fig. 5).

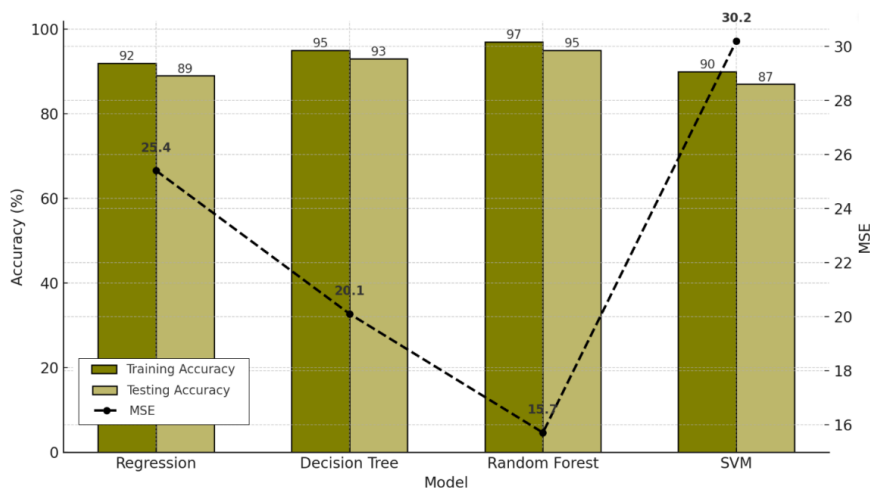


Fig. 5

Random Forest outperformed other models, with 97% training and 95% testing accuracy and the lowest mean squared error (15.7). Decision Tree also performed well, while Regression maintained stable generalization with acceptable error (25.4). SVM had slightly lower testing accuracy (87%) and higher MSE (30.2), reflecting its sensitivity to high-dimensional feature spaces. K-means clustering, as an unsupervised method, was excluded from MSE reporting but was valuable in customer pattern detection. Overall, model selection depends on the application context, but ensemble methods showed the best trade-off between accuracy and interpretability.

Discussion

The results of this study have shown that implementing DDDM in the textile manufacturing industry has significant operational, strategic, and environmental advantages. The results confirm the working hypothesis that predictive analytics, machine learning and integrated data systems can boost performance

across several key domains, including production efficiency, supply chain optimization, customer satisfaction and environmental sustainability.

There are such revelations, one of the most powerful would be the Avalanche 25% gain in quarterly output volume efficiency [17]. This reinforces the belief that the deployment of predictive maintenance and real-time monitoring would induce less machine downtime and better resource allocation.

In like manner, the 10% decrease in lead time and supply chain cost and a 33% reduction in backorder rates, supports the conclusion [19] stressing the importance of data-driven supply chain analytics in dealing with uncertainty.

From an environmental perspective, energy consumption, CO₂ emissions, and material waste were all significantly reduced, providing compelling evidence of the ecological efficacy of predictive sustainability models. The results are consistent with those [18, 25] that

suggested a sustainable textile operation framework with a circular economy perspective. The real-time monitoring techniques and closed-loop feedback systems used here shore up their theoretical propositions in real time. However, while existing research has concentrated mostly on recycling and reusing materials (and, to a lesser degree, upsizing material), the present work aims to observe sustainability in energy dynamic and water expenditure, therefore widening the environmental lens.

Gains for customer satisfaction, particularly in responsiveness (+12.2%) and overall satisfaction (+14.3%) warrant greater scrutiny, as well. These enhancements underscore the relationship between real-time data personalization and customer loyalty. As discussed [21, 23], and service personalization influences customer retention in digital industries to a large extent. This is a study that shows such principles also generalize to physical goods like textile products when machine learning models are integrated into post-sale communication systems.

The Random Forest model performed well, its black-box nature presents challenges in terms of interpretability, particularly for strategy planning teams that have not been trained in machine learning. This points to a more general problem mentioned by Marquesone and Carvalho [20] pointed out that the application of big data in the textile sector often lacks explainability which inhibits stakeholder adoption. Also, while k-means clustering worked for consumer segmentation, it assumes each data point, which may not reflect complex customer preferences in a more intricate marketplace.

In addition, the system's reliance on historical patterns can mitigate responsiveness to new disruptions like geopolitical events or sudden demand shifts. This is reminiscent of the concerns raised by Tawil et al. [22] which showed that when economic volatility faced UK-based SMEs, model inertia hindered the adoption of data-driven systems. Assimilating real-time anomaly detection and reinforcement learning can potentially address these constraints and improve adaptability.

Studies comparing international settings, notably in fast-developing economies would

bring much deeper comprehension of scalability and policy risks, as in the circular economy applications of Politi et al. [23].

Although the environmental statistics are encouraging, the models do not yet consider embedded carbon, supplier sustainability ratings, or life cycle assessment. Future iterations of the framework could be enriched with features like those proposed [24] provide support for ESG compliance tracking. As sustainability pressures mount worldwide, textile companies will likely need to move beyond internal efficiency metrics to include external sustainability disclosures and carbon credit modeling.

The findings of this study indicate that DDDM frameworks in textile production led to measurable improvements in operational, environmental, and customer-facing metrics. This is the future where predictive analytics, IoT infrastructure, and smart distribution integration give the entire industry more agility and greater sustainability.

Conclusion

DDDM improve all aspects of textile operations (production scheduling, supply chain coordination, consumer engagement, and sustainability optimization). By integrating supervised and unsupervised learning models, we were able to accurately forecast production costs, defect rates, and customer behavior patterns. Furthermore, through dimensionality reduction, fault identification, and entropy-based diagnostics, the monitoring of machine/process conditions was performed in real-time. This integrated data landscape enabled textiles management to take action based on insights that had either been previously inaccessible or hidden behind multiple data silos.

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