Enhancing textile industry efficiency using data mining and business intelligence for optimal supply chain management

DOI: 10.35530/IT.077.03.202554

P. VIJAYALAKSHMI
MANIMARAN S
KISHORE KUNAL
VAIRAVEL MADESHWAREN

ABSTRACT – REZUMAT

Enhancing textile industry efficiency using data mining and business intelligence for optimal supply chain management

In the modern textile industry, the integration of Business Intelligence (BI) through advanced Business Analytics (BA) and Data Mining (DM) techniques is crucial for enhancing supply chain management, optimising production efficiency, reducing operational costs and improving market responsiveness. By using data-driven decision-making techniques, clothing manufacturers can improve their production planning, inventory control and demand forecasting. Nonetheless, the textile industry frequently faces challenges such as unstructured data supply chain inefficiencies and unpredictable market trends, which can lead to increased waste and production delays. This study's main goal is to create a Python-based analytical framework that makes use of data mining methods to improve business intelligence and optimise production processes in the clothing industry. Over six months, production data quality control records and supply chain information were collected from three textile manufacturing facilities located in Trippur from SouthIndia. The gathered dataset was meticulously analysed using Python-based tools, including Pandas, Scikit-learn, and TensorFlow. Various techniques, such as clustering classification, association rule mining and predictive analytics, were employed to extract valuable insights. The research tested four key hypotheses that concentrated on production efficiency, demand prediction, raw material utilisation, and inventory optimisation. Machine learning models were applied to identify production bottlenecks, forecast sales trends and enhance inventory planning. The study's conclusions offer practical suggestions for raising operational effectiveness and profitability in the textile industry. Overall, this research highlights the transformative potential of business analytics in revolutionising textile manufacturing, fostering data-driven growth and strengthening competitiveness in the industry.

Keywords: *textile industry, business intelligence, data mining, predictive analytics, Python, supply chain optimisation*

Creșterea eficienței industriei textile prin utilizarea tehnicilor de explorare a datelor și Business Intelligence pentru o gestionare optimă a lanțului de aprovizionare

În industria textilă modernă, integrarea Business Intelligence (BI) prin intermediul tehnicilor avansate de Business Analytics (BA) și Data Mining (DM) este esențială pentru îmbunătățirea gestionării lanțului de aprovizionare, optimizarea eficienței producției, reducerea costurilor operaționale și îmbunătățirea capacității de reacție la cerințele pieței. Prin utilizarea tehnicilor de luare a deciziilor bazate pe date, producătorii de îmbrăcăminte își pot îmbunătăți planificarea producției, controlul stocurilor și previziunile privind cererea. Cu toate acestea, industria textilă se confruntă frecvent cu provocări precum datele nestructurate, ineficiențele lanțului de aprovizionare și tendințele imprevizibile ale pieței, care pot duce la creșterea deșeurilor și la întârzieri în producție. Obiectivul principal al acestui studiu este de a crea un cadru analitic bazat pe Python care utilizează metode de explorare a datelor pentru a îmbunătăți Business Intelligence și a optimiza procesele de producție în industria de îmbrăcăminte. Pe o perioadă de șase luni, au fost colectate date de producție, înregistrări de control al calității și informații privind lanțul de aprovizionare de la trei unități de producție textilă situate în Trippur, din sudul Indiei. Setul de date colectat a fost analizat meticulos folosind instrumente bazate pe Python, inclusiv Pandas, Scikit-learn și TensorFlow. Au fost utilizate diverse tehnici, precum clasificarea prin clustering, extragerea regulilor de asociere și analiza predictivă, pentru a extrage informații valoroase. Cercetarea a testat patru ipoteze cheie care s-au concentrat pe eficiența producției, previziunea cererii, utilizarea materiilor prime și optimizarea stocurilor. Au fost aplicate modele de învățare automată pentru a identifica blocajele din producție, a prognoza tendințele de vânzări și a îmbunătăți planificarea stocurilor. Concluziile studiului oferă sugestii practice pentru creșterea eficienței operaționale și a profitabilității în industria textilă. În ansamblu, această cercetare evidențiază potențialul transformator al analizei de afaceri în revoluționarea producției textile, în stimularea creșterii bazate pe date și în consolidarea competitivității în cadrul industriei.

Cuvinte-cheie*: industria textilă, Business Intelligence, explorarea datelor, analiza predictivă, Python, optimizarea lanțului de aprovizionare*

INTRODUCTION

The Indian garment business is seeing a very attractive market with a huge young consuming population of the fastest-growing nations in the world. The textile clothing sector plays a key part in developing countries like India, employing a large number of both unskilled and semiskilled people. The challenges in automating garment sewing due to constant alterations in patterns and stitching techniques have resulted in the industry's reliance on manual labour, rendering the clothing sector a typical entry-level industry that provides employment opportunities for developing nations due to its low fixed costs. In the 21st century, individuals focus more on self and social elements, which requires much of the (EQ) Emotional quotient than the (IQ) Intellectual quotient [1]. Every employee of a business at one point in time has to interact with their supervisors, subordinates, clients, colleagues, as well as other stakeholders on executing their tasks [2, 3]. It is crucial to recruit, maintain and motivate the most appropriate personnel inside the firm in order to achieve the corporate goals and objectives [4]. Supply chains serve two primary purposes: a market broker function that balances supply and demand, and a physical one centred on inventory management and transportation. Effective communication between suppliers and consumers is vital, acting as the foundation for Electronic Data Interchange (EDI), which promotes computer-to-computer transactions. Companies must know customer wants to build systems that link supply with demand [5].

To meet the growing demands of stakeholders for sustainability and the circular economy, fashion companies are rethinking their value chain, with a focus on how the transition from prompt to slower fashion business prototypes can result in an important change in the value they provide through development and distribution processes [6]. The multi-trillion-dollar textile and apparel business is increasingly globalised, with a focus on how the area may enhance various aspects of its GVC involvement to become a significant competitor in the industry's reconfiguration [7].

The textile and apparel (TandA) sector is widely acknowledged as a vital component of the global economy, making a substantial contribution to economic growth and job opportunities in low- and middle-income nations [8]. The epsilon-based measure (EBM) and the DEA-Malmquist productivity index (MPI) model were used to evaluate the performance of Vietnam's ten textile and apparel companies between 2017 and 2020. The proposed model was used to determine which companies performed the best and to increase their operational efficiency [9].

The textile, apparel, and fashion (TAF) sectors are a major contributor to worldwide pollution of the environment at every level of the supply chain, with stakeholders becoming increasingly aware of the impact these industries have on human rights and the climate [10].

A systematic analysis of 127 articles on sustainable supply chain management in the textile and apparel (T&A) industry focused on managing both economic and non-economic risks. Social and environmental ones are distinct [11]. In the examination of data-driven sustainable supply chain management (SSCM) indicators under industrial disruption and ambidexterity, the most important components were found to be resilience, financial vulnerability, and supply chain uncertainty risk assessment [12].

Utilising the revealed comparative advantage approach, the competitiveness of the Turkish textile industry was assessed, emphasising that export volume alone does not adequately determine an industry's competitiveness [13]. To investigate potential avenues for future research in the development of sustainable supply chain management (SSCM) in Indonesia's T&A industry, specifically in the small- and medium-sized enterprise (SME) sector, a systematic review was carried out [14]. A summary of sustainability assessment methods used in the textile and clothing industry was given, emphasising how most product-related assessment methods only considered environmental factors [15]. To lessen their environmental impact and obtain a competitive edge, producers of textiles and modern clothing are embracing and incorporating cutting-edge technologies. Most previous studies have ignored business intelligence systems (BIS) and instead concentrated on the larger picture of how big data might affect retail and distribution inside a firm, especially in the textile and apparel (T&A) industry [16].

METHODOLOGY

Data collection

Data was collected from three textile manufacturing facilities located in Trippur, Tamil Nadu, India, over six months (January 2023 – June 2023). The data encompassed three key areas: production data, quality control records, and supply chain information. Production data included details such as machine output, production time, downtime reasons, and resource utilisation. Quality control records comprised data on defects, rejection rates, and quality parameters. Supply chain information included data on raw material procurement, supplier details, delivery times, and inventory levels, which is explained in table 1. The data was collected in CSV format and stored in a secure database.

Table 1

DEMOGRAPHIC PROFILE OF DATA COLLECTION

Facility ID	Location (city)	Product specialization	Workforce size	Annual revenue (INR)
F001	Tirupur	Knitted garments	500	50 Crores
F002	Erode	Woven fabrics	350	30 Crores
F003	Karur	Home textiles	600	70 Crores

Research methodology

The primary components of the apparel global value chain are shown in the figure 1 below, which will aid in our analysis of all the processes involved in obtaining clothing from its inception through the phases of design, raw materials and intermediate inputs, marketing, and distribution to the end user. The garment

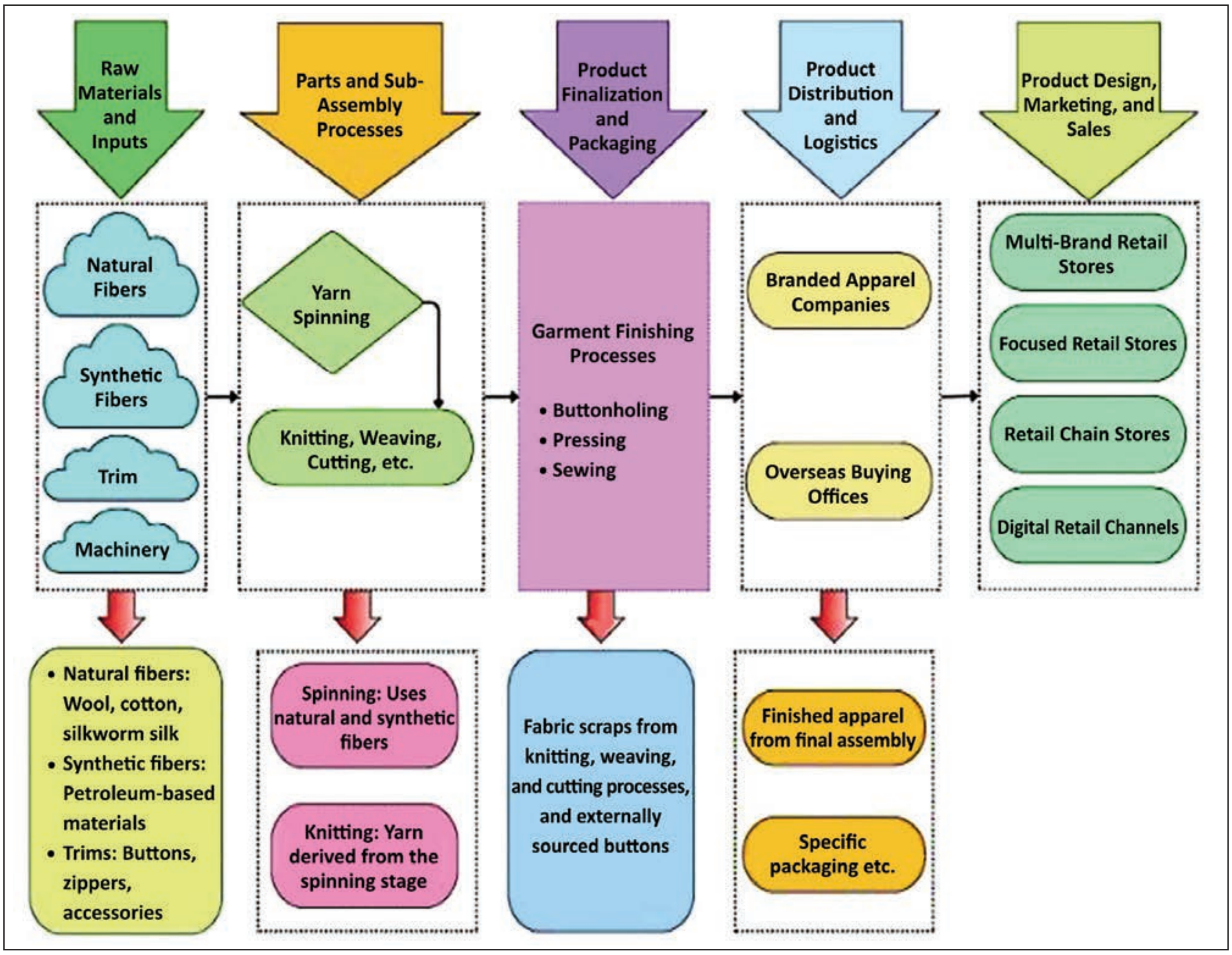


Fig. 1. Manufacturing and supply chain operations in Tamil Nadu's textile and apparel sector

chain often originates with huge stores holding established companies and distribution networks in countries that import them, which produce clothing ideas for approaching seasons. They then outsource operations to firms in developing countries to minimise costs. These manufacturers lack the brands and distribution methods to come to markets directly, which makes them reliant on the leading retailers, referred to as lead businesses. In the garment sector, innovation is generally focused on product design and marketing rather than manufacturing skills, enabling lead businesses to easily outsource production and keep substantial influence over the value chain. This dynamic describes the sector as a "buyer-driven" chain.

PROPOSED TECHNIQUES

Production batches were divided according to lead times, production efficiency and defect rates using clustering techniques, particularly K-Means clustering. The intention was to identify high-risk production categories and improve resource management by combining similar production batches

The K-Means algorithm iteratively assigns each data point x_i to one of K clusters by minimising the intra-cluster variance, represented as equation 1:

$$J = \sum_i = 1K \sum_{x_j \in C_i} ||x_j - \mu_i||2 \tag{1}$$

where x_j represents individual data points (e.g., production batches), μ_i is the centroid of cluster C_i, $||x_j - \mu_i||2$ is the squared Euclidean distance between a data point and the cluster centroid, and J is the total intra-cluster variance that the algorithm minimises. Figure 2 shows the production process of apparel.

By using K-Means clustering, the textile industry could optimise inventory planning and schedule maintenance more effectively by analysing trends in defect rates.

Classification

To predict defective batches based on historical inspection records, Decision Tree and Random Forest classifiers were implemented. Automated defect prediction was made possible by these classification techniques, which enhanced quality control and decreased the need for manual inspections. A tree-like structure is created by the Decision Tree algorithm to classify production batches, with each node representing a decision rule based on input features like machine temperature, humidity, raw material quality and operator skill. The following equation 2 is used to determine the likelihood that a batch falls into a particular defect category:

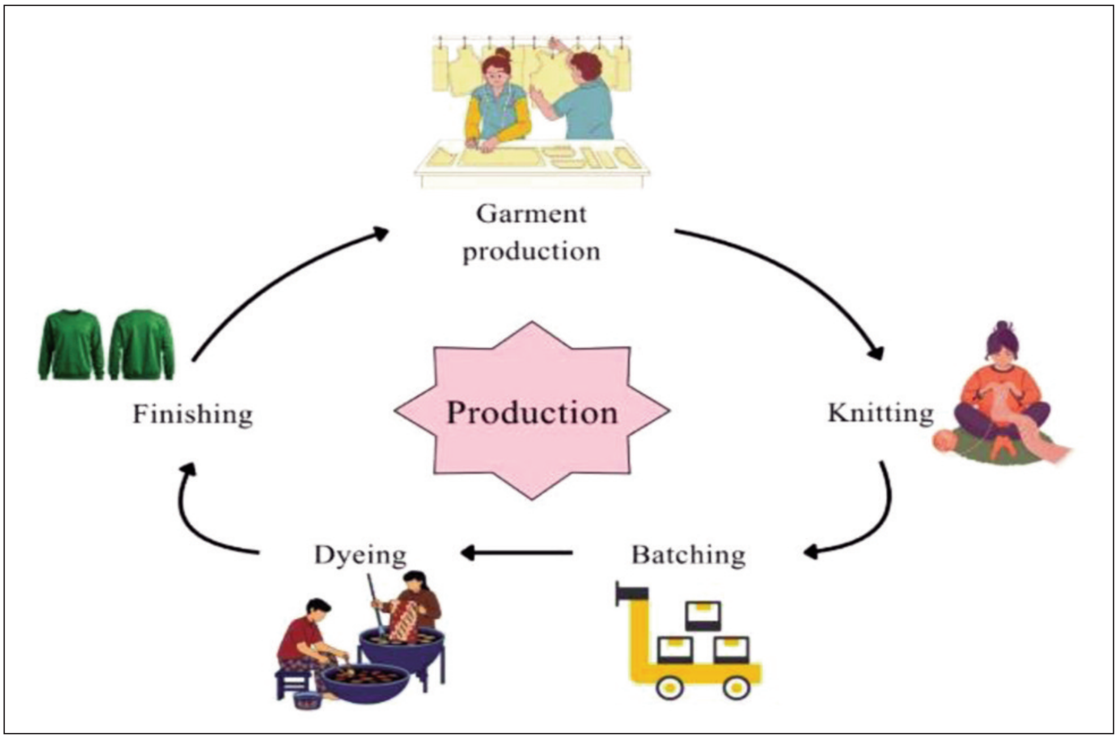


Fig. 2. Production process of apparel

$$P(C_k \mid X) = \frac{N_{C_k}}{N} \quad (2)$$

where $P(C_k \mid X)$ is the probability of class C_k (defective or non-defective) given feature set X, N_{C_k} is the number of instances belonging to class C_k, and N is the total number of instances in the dataset.

LSTM technique

The LSTM has three controllers or gates: IOF, in addition to a long memory cell. The input gate is responsible for determining what extra information should be retained in the cell state. It uses the current input data from the previous period and removes data about irrelevant factors. Finding data that is no longer necessary in the unit state allows the forget gate to calculate the forget vector. Lastly, the output gate determines the output. The following are the main LSTM equations. The forget gate decides which data should be removed from the cell state, which is expressed in equation 3.

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \quad (3)$$

Equation 4 chooses which newly acquired data should be kept in the cell state.

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \quad (4)$$

Equation 5 adds new information to the cell state.

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \quad (5)$$

Equation 6 figures out the current time steps output.

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \quad (6)$$

where x_t represents the input at time t, h_{t-1} is the hidden state from the previous time step, W_f, W_i, W_o are weight matrices, b_o are bias terms, and σ is the sigmoid activation function.

The textile industry could enhance supply chain efficiency, predict changes in market demand and optimise inventory management by putting LSTM-based predictive analytics into practice. In the textile industry, the application of cutting-edge data mining techniques greatly enhanced quality control, production efficiency and decision-making.

Classification improved defect prediction, association rule mining revealed important machine failure patterns, clustering made resource allocation easier and predictive analytics improved sales forecasting. Textile producers increased operational effectiveness, decreased waste and increased profitability by utilising these strategies.

Validation of the model

Standard evaluation metrics were used to evaluate the predictive models' performance. The Scikit-learn metrics library was used to compute the classification models' accuracy, precision, recall and F1-score (equation 7):

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \quad (7)$$

where y_i is the actual value and $\hat{y}_i$ is the predicted value.

Hypotheses

The hypothesis used for this research was:

- *H1: Data-driven decision-making significantly improves operational efficiency in textile manufacturing.*

- *H2: Enhanced business intelligence frameworks contribute to better demand forecasting and inventory management.*
- *H3: The adoption of business analytics reduces raw material wastage and optimises supply chain efficiency.*
- *H4: Predictive insights lead to improved production planning and reduced market response delays.*

RESULTS

Hypothesis 1 analysis

Table 2 analysed the impact of Business Intelligence on production efficiency for hypothesis 1. The metric used for this research was Average Machine Utilisation (%), Downtime Reduction, Production Cycle Time, Defect Rate Reduction (%), and Energy Consumption Reduction (%). These metrics were analysed for facility F001 (knitted garments), Facility F002 (Woven Fabrics), and Facility F003 (Home Textiles). Facility F002 had a lower utilisation of 78.3% and a longer cycle of 14.8 hours, while Facility F001 had the highest machine utilisation of 85.6% with a production cycle of 12.2 hours. Facility F003 demonstrated an 82.1% utilization rate, the most effective downtime reduction of 18.2%, and a 13.3% energy savings. With F003 at 10.5%, F001 at 9.7%, and F002 at 8.3% defect rates also improved.

Hypothesis 2 analysis

Table 3 illustrates the forecast accuracy for demand prediction for hypothesis 2. Here, the LSTM neural network has 2.15 MAE, 3.28 RMSE, and 4.6% MAPE, which outperformed the best compared to the other 2 techniques. The random forest regression model effectively captured nonlinear historical relationships and had moderate error rates. On the other hand, the traditional moving average approach performed the worst, failing to take seasonality into account, and the ARIMA model showed higher error rates, indicating difficulty adjusting to demand fluctuations. Overall, the findings support Hypothesis 2, demonstrating that more accurate demand projections are produced by sophisticated forecasting models.

Hypothesis 3 analysis

Optimisation strategies driven by Business Intelligence (BI) have significantly improved raw material efficiency across various categories, which is shown in table 4 and figure 3. Cotton utilisation was highest in facility F003 at 90.2%, indicating reduced

Table 2

IMPACT OF BUSINESS INTELLIGENCE ON PRODUCTION EFFICIENCY (HYPOTHESIS 1)

Metric	Facility F001 (Knitted garments)	Facility F002 (Woven fabrics)	Facility F003 (Home textiles)
Average machine utilisation (%)	85.6%	78.3%	82.1%
Downtime reduction (%)	15.4%	12.8%	18.2%
Production cycle time (hrs)	12.2	14.8	13.1
Defect rate reduction (%)	9.7%	8.3%	10.5%
Energy consumption reduction (%)	12.1%	10.5%	13.3%

Table 3

FORECAST ACCURACY FOR DEMAND PREDICTION (HYPOTHESIS 2)

Forecasting model	MAE (Mean Absolute Error)	RMSE (Root Mean Square Error)	MAPE (Mean Absolute Percentage Error)
LSTM Neural Network	2.15	3.28	4.6%
ARIMA Model	3.42	4.86	6.1%
Random Forest Regression	2.87	4.02	5.3%
Traditional Moving Average	5.23	7.41	8.9%

Table 4

OPTIMIZATION OF RAW MATERIAL UTILIZATION (HYPOTHESIS 3)

Raw material	Facility F001 – Utilization efficiency (%)	Facility F002 – Utilization efficiency (%)	Facility F003 – Utilization efficiency (%)
Cotton	89.4	86.1	90.2
Polyester	84.2	80.5	85.6
Rayon	88.1	82.7	89.5
Wool	81.3	79.2	84.1
Blended fibers	87.8	84.9	88.2

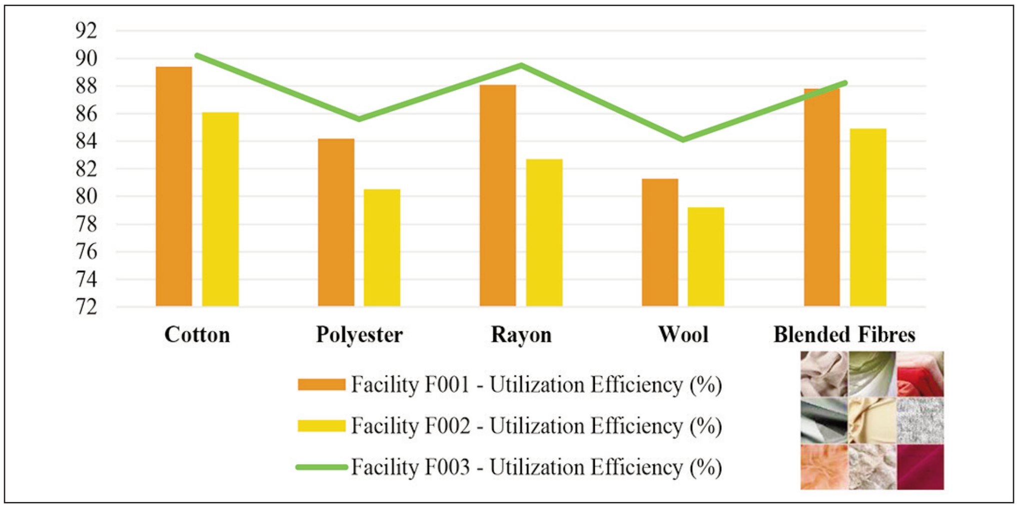


Fig. 3. Optimization process

wastage in home textile production. Polyester utilisation showed a marked improvement, particularly in F003 at 85.6%. Rayon also performed well with efficiencies of 88.1% and 89.5% in F001 and F003, respectively.

In F002, wool utilisation was lower at 79.2%, but the system handled variability well. Blended fibres achieved high efficiencies with F001 at 87.8% and F003 at 88.2%. Overall, BI has notably enhanced raw material utilisation, affirming hypothesis 3.

Hypothesis 4 analysis

The effectiveness of inventory optimisation for hypothesis 4 was explained in table 5. Here, the stock turnover ratio was 5.2% in before Business Intelligence implementation, and 7.8% in after BI implementation. So totally the improvement % was 50% for the stock turnover ratio. Then 1.2 M and 850 K for holding cost reduction (INR) for both before and after BI implementation. The improvement of Holding Cost Reduction was 29.2%. Lead time (days) was reduced from 14 to 10 before and after BI implementation. The range improvement was 28.6%. And finally, the overstock reduction of before and after was 18.2% and 9.4%, and the overall improvement was 48.4%.

Process-wise performance evaluation in textile manufacturing

Table 6 illustrates the significant operational variation found in the evaluation of textile manufacturing processes. Important results show that knitting took an average of 11.5 hours with a 5.2% defect rate, while dying took the longest at 14.2 hours with a 7.8% defect rate. Printing required 12.7 hours with a 6.3% defect rate, and cutting proved efficient with just 9.8 hours and 4.9% defects. It took 13. 4 hours to sew with a 5.6% defect rate and 10.9 hours to finish with a 4.1% defect rate. Packaging was the fastest at 8.6 hours, achieving the lowest defect rate of 3.5%. Different efficiency and quality metrics are highlighted in the assessment, suggesting areas for process optimisation.

Business intelligence impact on supply chain metrics

Table 7 demonstrates the Business Intelligence Impact on Supply Chain Metrics. Supplier Lead Time (days), On-time Delivery (%), Procurement Cost Reduction (INR), and Order Fulfilment Rate (%) were the supply chain parameters utilised in this study. The supplier lead time was 12 days before BI installation and 8 days after BI implementation, which have 33.3% improvement. The on-time was better after BI installation, which 91% and 78% in before BI deployment. The procurement cost reduction has improved by 24%, and it was 1.9 million before and 2.5 million after BI adoption. And lastly, the order fulfilment rate fared best after BI deployment, which has 14.6% improvement.

Table 5

EFFECTIVENESS OF INVENTORY OPTIMIZATION (HYPOTHESIS 4)

Inventory parameter	Before BI implementation	After BI implementation	Improvement (%)
Stock turnover ratio	5.2	7.8	50%
Holding cost reduction (INR)	1.2 M	850 K	29.2%
Lead time (days)	14	10	28.6%
Overstock reduction (%)	18.2%	9.4%	48.4%

Table 6

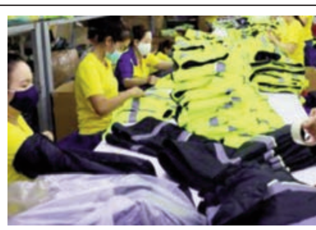
PROCESS-WISE PERFORMANCE EVALUATION IN TEXTILE MANUFACTURING				
Process	**Picture**	**Avg. production time (hrs)**	**Defect rate (%)**	**Resource utilization (%)**
Knitting		11.5	5.2	87.3
Dyeing		14.2	7.8	82.5
Printing		12.7	6.3	85.2
Cutting		9.8	4.9	89.7
Sewing		13.4	5.6	86.1
Finishing		10.9	4.1	90.2
Packaging		8.6	3.5	91.3

Table 7

BUSINESS INTELLIGENCE IMPACT ON SUPPLY CHAIN METRICS			
Supply chain parameter	**Before BI implementation**	**After BI implementation**	**Improvement (%)**
Supplier lead time (days)	12	8	33.3
On-time delivery (%)	78	91	16.7
Procurement cost reduction (INR)	2.5 M	1.9 M	24
Order fulfilment rate (%)	82	94	14.6

CONCLUSION

The implementation of business intelligence (BI) in the textile sector has led to significant improvements in production and supply chain operations. Facility F001 achieved higher machine utilisation rates and shorter production cycle times, indicating more effective operational procedures according to analysis. Facility F003 experienced notable reductions in energy consumption and equipment downtime, illustrating BI's effectiveness in detecting and resolving hidden inefficiencies. Optimisation of material usage was particularly pronounced in Facility F003, especially for cotton and rayon, while Facility F002 identified further improvement opportunities. In terms of inventory management, BI-driven predictive analytics, especially LSTM-based demand forecasting, allowed for more efficient stock turnover, lower inventory holding costs and lower levels of excess inventory. In examining production processes, packaging was found to be highly efficient; however, dyeing processes require further refinement to lessen defects and energy usage. Enhancements in procurement strategies, shorter lead times, and improved reliability in deliveries have collectively bolstered supply chain performance, leading to faster and more dependable order fulfilment. Overall, the adoption of BI has not only enhanced operational efficiency but also fostered a more agile, cost-effective and future-oriented manufacturing environment, thereby reinforcing long-term competitiveness.

ACKNOWLEDGEMENT

I would express my gratitude to my guide, co-authors and institutions for their continual support in writing this research.

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Authors:

P. VIJAYALAKSHMI[1], MANIMARAN S[1], KISHORE KUNAL[2], VAIRAVEL MADESHWAREN[3]

[1]Department of Management Studies, PSNA College of Engineering and Technology, Kadiranampatti, Dindigul, Tamil Nadu, India

[2]Professor and Dean of Online Education, Loyola Institute of Business Administration (LIBA), Loyola College Campus, Nungambakkam, Chennai, Tamil Nadu, India

[3]Department of Agriculture Engineering, Dhanalakshmi Srinivasan College of Engineering, Coimbatore, Tamil Nadu, India

Corresponding author:

P. VIJAYALAKSHMI
e-mail: Viji2025guide@induniversityedu.org