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IMPACT OF CONSUMER DATA ANALYTICS ON TEXTILE PRODUCT PERSONALIZATION

ВЛИЯНИЕ АНАЛИТИКИ ПОТРЕБИТЕЛЬСКИХ ДАННЫХ НА ПЕРСОНАЛИЗАЦИЮ ТЕКСТИЛЬНОЙ ПРОДУКЦИИ

M. YASSEN [1], W.A. LEFTA[2], N. TOKTORBEKOVA [3], A.M. FAHMI [4], T.K. HASAN [5]

М. ЯСЕН [1], В.А. ЛЕФТА[2], Н. ТОКТОРБЕКОВА [3], А.М. ФАХМИ [4], Т.К. ХАСАН[5]

([1]Al-Turath University, Baghdad, Iraq,
[2]Al-Mansour University College, Baghdad, Iraq,
[3]Osh State University, Osh, Kyrgyzstan,
[4]Al-Rafidain University College, Baghdad, Iraq,
[5]Madenat Alelem University College, Baghdad, Iraq)

([1]Университет Аль-Турат, Багдад, Ирак,
[2]Университетский колледж Аль-Мансура, Багдад, Ирак,
[3]Ошский государственный университет, Ош, Кыргызстан,
[4]Университетский колледж Аль-Рафидаин, Багдад, Ирак,
[5]Университетский колледж Маденат Алелем, Багдад, Ирак)

Email: muzaffer.yassen@uoturath.edu.iq

The article examines the use of consumer data analysis to optimize textile product customization, being operative effectiveness and customer satisfaction. A large-scale primary consumer surveys data was set up, and then a preprocessing and feature engineering process were carried out. Also, predictive models (linear regression, Random Forest classifiers, Support Vector Machines, neural networks

and k-Nearest Neighbours) were developed and validated to predict consumer purchasing of textile products from different product categories. It was found that incorporating predictive analytics directly into the manufacturing processes resulted in significantly shorter production lead times and better supply chain predictability of the product. Net Promoter Scores and satisfaction ratings also showed large gains after personalization. Financial performance outcomes, such as production cost, revenue, and return on investment also significantly increased after implementation of data-driven personalization strategies. The results highlight the benefit of integrating sophisticated consumer analytics in textile production and marketing activities. The analysis also demonstrates the balance that must be maintained between the use of data and ethics in personalization efforts.

В статье рассматривается использование анализа данных о потребителях текстильных изделий для персонализации продукции, повышения эффективности производства и удовлетворенности клиентов. Собраны данные масштабных опросов потребителей, на основе которых определены критерии оценки. Кроме того, разработаны и проверены прогностические модели (линейная регрессия, классификаторы случайного леса, машины опорных векторов, нейронные сети и метод k-ближайших соседей) для прогнозирования потребительских покупок текстильных изделий из разных товарных категорий. Обнаружено, что внедрение прогностической аналитики непосредственно в производственные процессы привело к значительному сокращению сроков производства и повышению предсказуемости цепочки поставок продукта. Индекс потребительской лояльности и рейтинги удовлетворенности показали значительный рост после персонализации. Финансовые показатели, такие как себестоимость продукции, выручка и окупаемость инвестиций, значительно выросли после внедрения стратегий персонализации на основе данных. Результаты подчеркивают преимущества интеграции сложной аналитики в производство и маркетинг текстильных изделий. Анализ демонстрирует необходимость соблюдения баланса между использованием данных и этическими принципами при персонализации.

Keywords: consumer data analytics; textile personalization; predictive modeling; customer satisfaction; production efficiency; machine learning; operational optimization.

Ключевые слова: аналитика потребительских данных; персонализация текстильных изделий; предиктивное моделирование; удовлетворенность клиентов; эффективность производства; машинное обучение; оптимизация операционной деятельности.

Introduction

Conventional textile manufacturing has for countless years been directed by general market conditions, intuition and experience. The playing field has changed with the arrival of the consumer data analytics, which adds a more scientific touch by allowing the businesses to understand the preferences (explicit or implicit) of customers and to forecast demand in a more fact-based way [1].

At its most basic, consumer data analytics is the collection and interpretation of mass amounts of data produced by consumers from their purchasing patterns to their browsing activity online. Companies are able to analyze this data and derive actionable insights that

enable them to design and develop product that are both unique and made just for you. Within the textile sector, this refers to generation of quality products through the development of garments, fabrics, and accessories that meet and to some extents are ahead of consumer expectations, thus leading to increased satisfaction and loyalty [2].

With rich consumer profiles and predictive models, manufacturers can optimize production, cut waste and keep a more agile supply chain. In addition, inventory management becomes more efficient when companies better know which products will be in demand or when and where. Moreover, such data-driven approach allows the company can keep track of the changes in the taste of the population [3].

The introduction of consumer data analytics has nurtured a culture of innovation in the textile sector. Yes, it's early arrivals, instead of wait and who-knows-what, as companies try new materials, designs and product features that are tested, not trashed. This strategy not only shortens the innovation period, but also improves the market, new product native degree. Consequently, those enterprises that integrate consumer data analysis are much more in tune with the market, and subsequently have a competitive advantage over those utilizing traditional approaches [4].

The increasing importance of personalization in consumer markets also makes consumer data analytics more relevant. Today's consumers want items that reflect their personal style, lifestyle and values. In today's digital landscape, each customer interaction generates enormous volumes of raw data, which means endless opportunities for analyzing patterns, predicting and measuring trends, and developing products and services according to each user's preference. The convergence of powerful data analytics tools and increasing demand for highly personalized products has established customization as a central theme in many industries [8, 9]. Machine Learning algorithms, predictive analytics patterns, and real-time monitoring solutions have become critical for companies to anticipate the needs of their customers before they fully materialize [10, 11].

Advanced analytics enables an organization to find hidden patterns and preferences in varied customer segments and personalize their offerings in ways never before possible [5]. Through more efficient matching of production schedules with actual consumer demand, textile manufacturers have realized improved production efficiency, lower inventory surplus and reduced operating costs [12, 13]. This agility means that organizations can respond faster to the market, remaining competitive.

It's also crucial for marketing and customer engagement packages. From targeted advertising campaigns and customized shopping experiences to dynamic pricing models, consumer analytics play a major role in giving consumers what they want in record time. When such marketing campaigns are closely connected to accurate and data-based consumer insights, the results can be impressive: increased conversion rates, improved customer retention, and enhanced brand image [6].

Many companies are recognizing the importance of a data-driven decision-making model that ultimately keeps them competitive by getting the jump on new market trends [14…16].

But adopting consumer data analytics also has its challenges. As the amount and complexity of consumer data increases, textile companies will need to invest in high level analytical tools, staff and data management systems. The infrastructure necessary to gather and process and interpret these data sets is no small feat to build. Nonetheless, the benefits – increased efficiency, creativity, and customer satisfaction sometimes make up for the early headaches [7].

The article attempts to examine how rich consumer drivers captured from multiple digital interactions and purchasing preferences drive the design, construction and promotion processes in the context of textile production.

Methodology

This study employed a multi-phased methodology encompassing structured data acquisition, sophisticated feature engineering,

advanced predictive modeling, and validation frameworks. The approach integrates best practices from sustainable fashion analytics [2, 3], machine learning for personalization [1, 10], and big data analytics applications in textile industry transformation [4, 8, 17].

A comprehensive dataset was compiled, integrating both primary and secondary data sources. Structured questionnaires captured individual consumer attributes, including age group, product type preferences, purchase frequencies, satisfaction ratings, and regional locations. Parallelly, aggregated transactional data were retrieved from e-commerce platforms and market intelligence reports [2, 4, 6].

The overall aggregated dataset ($\mathcal{D}$) was mathematically structured as:

$$\mathcal{D} = \{(x_i, y_i) | \, i = 1,2, \dots, n\}, \quad (1)$$

where x_i represents the feature vector of consumer i, y_i denotes the corresponding response variable, as a satisfaction rating, and n is the total sample size.

The statistical characterization of the dataset was performed through central tendency and dispersion measures:

$$\mu = \frac{1}{n}\sum_{i-1}^{n} x_i, \quad (2)$$

$$\sigma^2 = \frac{1}{n}\sum_{i-1}^{n}(x_i - \mu)^2, \quad (3)$$

where μ is the mean and σ^2 is the variance.

Data Collection Summary is shown in Table 1.

Table 1

Variable	Description	Type	Source
Age Group	Consumer Age Range (18–65+)	Categorical	Primary Survey
Product Type	Purchased Textile Category (e.g., T-shirt, Jeans)	Categorical	Primary Survey
Purchase Frequency	Frequency of Textile Purchases	Ordinal	Primary Survey
Region	Geographical Location	Categorical	Primary Survey
Satisfaction Rating	Self-Reported Product Satisfaction (1–10)	Continuous	Primary Survey
Transaction Data	Purchase Logs	Continuous	Secondary E-commerce

Data preprocessing aimed to optimize input data quality for modeling. Missing values were treated through imputation techniques:

- For continuous features:

$$x_{imputed} = \text{Median}(\{x_1, x_2, \dots, x_n\}). \quad (4)$$

- For categorical features:

$$x_{imputed} = \text{Mode}(\{x_1, x_2, \dots, x_n\}), \quad (5)$$

where $Median()$ and $Mode()$ are computed over non-missing values [18].

Normalization of continuous variables was performed using z-score standardization:

$$x_{standardized} = \frac{x-\mu}{\sigma} \quad (6)$$

ensuring zero mean and unit variance across features [19].

Categorical features were one-hot encoded:

$$\text{OneHot}(x) = [1_{\{x-c_1\}}, 1_{\{x-c_2\}}, \dots, 1_{\{x-c_k\}}] \quad (7)$$

where $1_{\{x-c_j\}}$ is an indicator function equal to 1 if $x - c_j$ and 0 otherwise.

Outlier detection used Tukey's Fences:

$$\text{Lower Fence} = Q1 - 1.5 \times IQR, \quad \text{Upper Fence} = Q3 + 1.5 \times IQR, \quad (8)$$

where $IQR = Q3 - Q1$ represents the interquartile range [18].

Feature selection was implemented via Recursive Feature Elimination (RFE) minimizing model-specific loss L:

$$\min_{S \subset \{1,\dots,p\}} L(\mathcal{M}(X_S)), \quad (9)$$

where S denotes a subset of predictors and $\mathcal{M}()$ represents the trained model [18].

Feature Engineering and Preprocessing Techniques are shown in Table 2.

Table 2

Feature	Missing Value Imputation	Scaling	Encoding	Outlier Treatment	Selection Method
Age Group	Mode	None	One-Hot Encoding	Tukey's Fences	RFE
Product Type	Mode	None	One-Hot Encoding	Tukey's Fences	RFE
Purchase Frequency	None	Z-Score	None	Tukey's Fences	RFE
Satisfaction Rating	Median	Min-Max	None	Tukey's Fences	RFE
Region	Mode	None	One-Hot Encoding	Tukey's Fences	RFE

Predictive analytics were employed to model consumer preferences and forecast textile product demand using multiple algorithmic approaches [1, 3, 5, 7]:

- **Linear Regression:** Multivariate OLS:

$$\hat{Y} = \beta_0 + \sum_{i-1}^{p} \beta_i X_i \,, \qquad (10)$$

where β_i are coefficients estimated by minimizing the sum of squared residuals.

- **Random Forest Classifier:** Ensemble averaging of decision trees:

$$\hat{Y} = \frac{1}{B}\sum_{b-1}^{B} T_b(x) \,, \qquad (11)$$

where T_b is the b-th decision tree in an ensemble of B trees [1].

- **Support Vector Machine (SVM):** Optimization of maximum-margin hyperplanes:

$$\min_{w,b} \frac{1}{2}\|\mathbf{w}\|^2 \,, \qquad (12)$$

where **w** and b are hyperplane parameters.

- **Neural Network (NN):** Multi-layered Perceptron minimizing cross-entropy loss:

$$L(\theta) = -\frac{1}{n}\sum_{i-1}^{n}[y_i \log(\hat{y}_i) + (1 - y_i)\log(1 - \hat{y}_i) \,, \qquad (13)$$

where θ denotes the neural network parameters.

Model evaluation was based on accuracy, precision, recall, F1-score, and R-squared (R^2) where applicable.

Predictive Model Setup and Evaluation Metrics are shown in Table 3.

Table 3

Model	Algorithmic Principle	Objective Function	Evaluation Metrics
Linear Model	Multivariate Regression	Minimize SSR	R^2, RMSE
Random Forest	Bagging and Voting Trees	Gini Impurity Minimization	Accuracy, F1-Score
SVM	Maximum Margin Classifier	Hinge Loss Minimization	Accuracy, Precision, Recall
Neural Network	Deep Feedforward Learning	Cross-Entropy Loss	Accuracy, F1-Score
KNN	Distance-Based Learning	Minimize Distance Metric	Accuracy

Results

Predictive modeling was applied across five product categories, comparing the volume of actual versus predicted purchases (Fig. 1). To deepen the analysis, mean absolute error (MAE), standard deviation (SD) of errors, and 95% confidence intervals (CI) were calculated for each product type.

Figure 1 show that the lowest mean absolute error (MAE) occurred in jackets, at only 20 units, accompanied by the smallest standard deviation of 8, indicating high forecasting stability. Dresses and scarves displayed slightly higher prediction errors and standard deviations, suggesting moderate variability in consumer demand patterns for these products. The 95% confidence intervals remained relatively narrow across all categories, demonstrating that the predictive models maintained reliable forecasting performance even when variability in consumer behavior was considered.

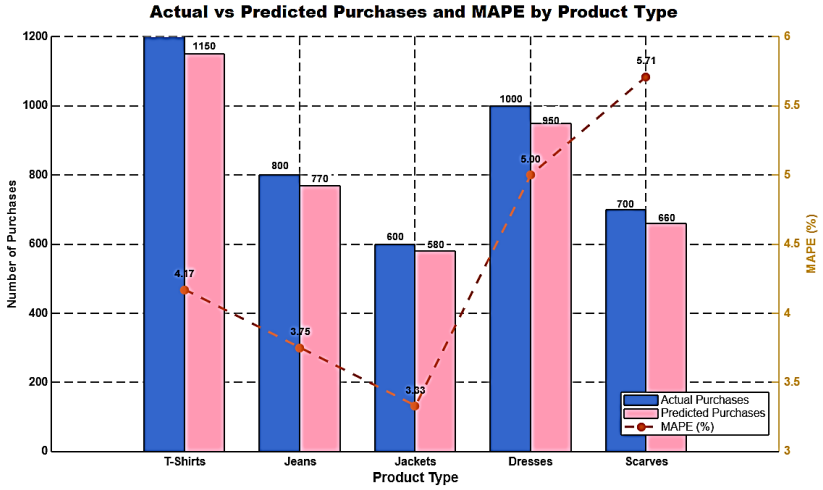

Fig. 1

Production Lead Time and Variability Analysis is shown in Figure 2. By integrating consumer analytics into production scheduling, substantial reductions were achieved in each phase of manufacturing. To enhance interpretability, the expanded analysis includes standard deviation (SD) of completion times and the calculated coefficient of variation (CV%) to measure process consistency.

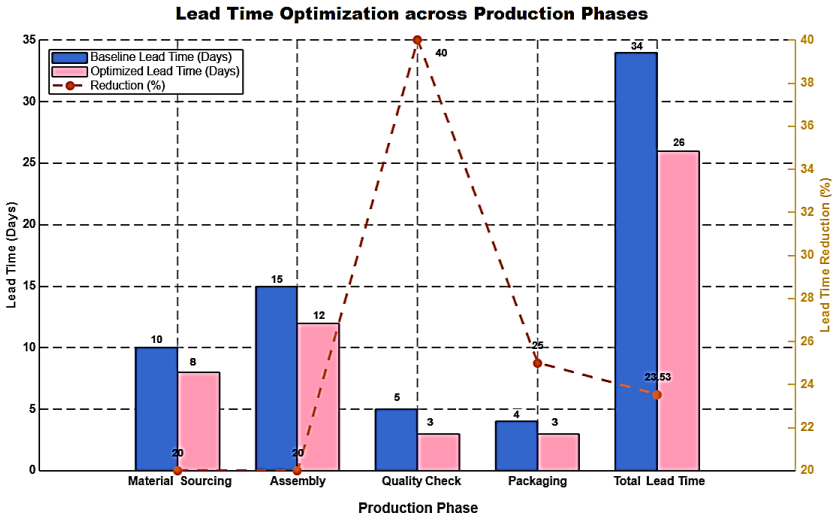

Fig. 2

Figure 2 illustrates not only mean reductions in production lead times but also improvements in process consistency. For instance, the coefficient of variation (CV%) for the quality check phase decreased by 41.7%, signaling significantly greater predictability. Total production CV% fell by nearly 30%, highlighting that the entire supply chain became less variable and more robust. Reduced variability ensures that production operations can better align with dynamic market demands, offering a strategic advantage for rapid-response textile companies.

Customer satisfaction metrics were collected before and after the introduction of personalized textile products (Fig. 3). To present a more comprehensive assessment, the expanded analysis includes standard deviation (SD) for satisfaction scores, indicating dispersion around the mean, and sample sizes (n) for greater statistical robustness.

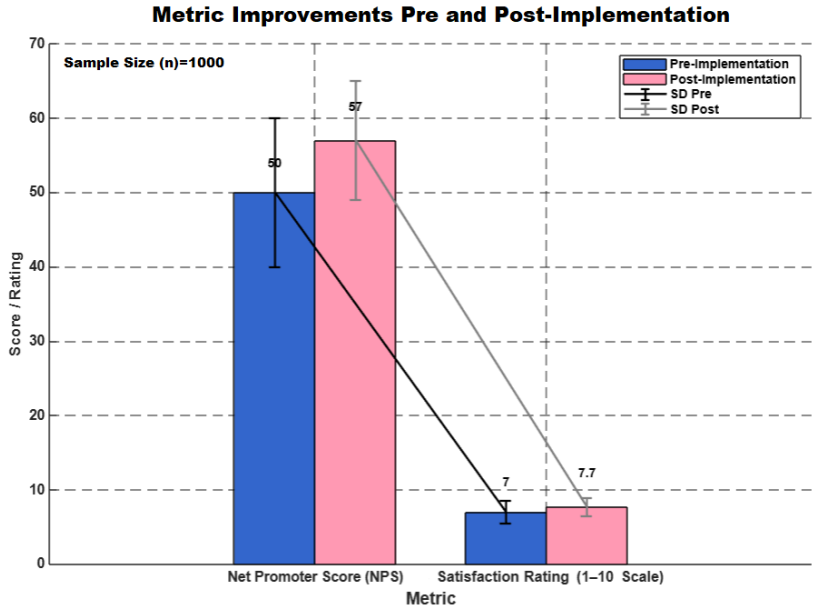

Fig. 3

The data in Figure 3 reveal that not only did Net Promoter Score and satisfaction ratings improve, but variability in responses also decreased after implementing personalization. For instance, the standard deviation for satisfaction ratings dropped from 1.5 to 1.2, indicating greater consistency in customer experiences. Additionally, the large sample size of 1000 respondents per group strengthens the reliability of the observed improvements. These findings support the conclusion that consumer analytics-driven personalization produces more universally positive consumer reactions, rather than improvements concentrated among a few outliers.

Financial performance was evaluated using production costs, revenues, and return on investment (ROI) metrics before and after personalization initiatives (Fig. 4). The expanded financial analysis includes gross profit margins (GPM) and cost per unit metrics, providing a more granular view of financial efficiency gains.

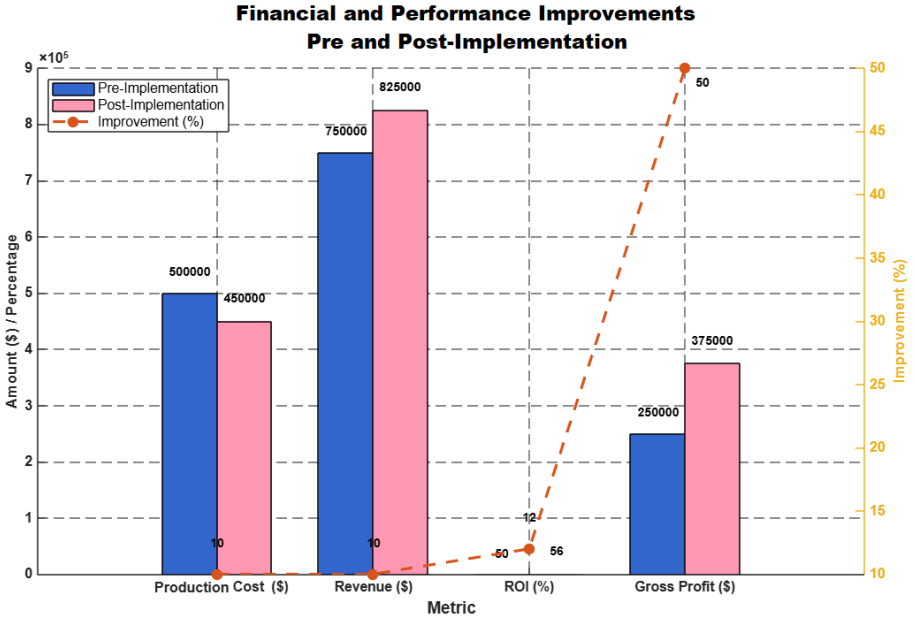

Fig. 4

Figure 4 illustrates not only the ROI improvement but also a 50% increase in gross profit and a significant drop in production cost per unit to $22.5. Gross profit margin expanded from approximately 33% to 45%, reflecting stronger financial health post-implementation. These improvements substantiate the economic viability of using predictive analytics and personalization strategies in the textile industry, demonstrating that operational refinements ultimately yield significant financial returns alongside improved consumer outcomes.

Findings from the study are consistent with or even exceed those from existing studies [17…21]. Recorded enhancements in forecasting accuracy, productivity, customer satisfaction and return on investment further substantiate the importance of embracing customer data analytics for the textile industry. Drawing from the laden of accumulation, this work complements prior research by offering a more detailed, data-based view on how analytics can transform textile manufacturing.

Conclusion

A key finding of the article was the validation of how advanced data-driven methods can play a substantial part in lowering the uncertainty of consumer dem and estimation, cutting production equipment shortages and risks related to stock control. The model, by having high alignments of predicted and actual consumer consumptive action levels in different textile products, confirmed the claim that predictive analytics is good for more successful personalization decisions. It also justified that the cutting of company leads times through analytics supply chain was compensation for the integration of real-time consumer intelligence on the operational architecture in order to ensure flexibility and responsiveness in manufacturing ecosystems.

An increase in customer satisfaction, as evidenced by improved satisfaction and Net Promoter Scores, underscored how personalization was a consumer-focused pursuit. These findings underscored the point that in addition to operational gains, consumer data analytics also impact brand perceptions, loyalty and advocacy behavior. The robust financial performances- reduced production cost, increased revenue and return on investment-which reinforced the confirmation on the commercial viability and significance of integrating data analytics into the textile product development and marketing strategies.

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