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## ADOPTION OF AUTOMATION AND SMART TECHNOLOGIES IN MODERN TEXTILE PRODUCTION SYSTEMS

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### ABSTRACT

Automation, artificial intelligence, connected sensing technologies, digital twins, robotics, and data-driven control systems are increasingly transforming textile and apparel production systems. However, in existing studies, these technologies have often been analyzed separately or limited to specific factories, countries, or specific stages of the production process. The study created an integrated analytical framework for analyzing the maturity of technology adoption in modern textile production systems, with a new dataset based on data collected from various sources related to technology adoption and digital readiness open to the public. The complete dataset contains a total of 8,198 analytical observations and 26 variables. The dataset covers nine manufacturing and business activities for the period 2019-2023 in five countries - Bangladesh, Chile, Ethiopia, India and Senegal. As part of this study, a subset of 5,472 production-based observations were used for predictive modeling. This subset is divided into 3,830 trainings, 821 validations, and 821 test observations, respectively, in a group-conscious manner. The study compared the performance of four models: Random Forest, XGBoost, Support Vector Machine and One-Dimensional Convolutional Neural Network (1D CNN). The final results showed 92.00%, 93.00%, 93.56% and 96.10% accuracy respectively, making 1D CNN the highest performing model. In a test set of 821 observations, 1D CNN's class-based F1 score was 95.29% for Basic / Manual, 97.54% for Intermediate / Mechanized, 68.57% for Digital, and 95.20% for Advanced / Smart. In the supplied ROC analysis, the value of AUC was found to be 0.998094. Integrated Gradients-based Explainable AI analysis also indicates that country-specific context, clothing cutting and sewing activities, production-domain indicators, quality-management-related variables, survey duration, and internet access rate contribute significantly to model decisions. Overall, the results show that it is possible to effectively analyze the maturity of technology adoption by combining various publicly available technology indicators with machine learning and deep learning. At the same time, class inequalities and limitations in the comparability of data from different countries have also been identified, which are important considerations for future research and external verification.

**Keywords:** Textile Automation; Smart Manufacturing; Industry 4.0; Technology Adoption; Explainable AI

## 1 INTRODUCTION

Textile and apparel manufacturing is undergoing a transition from labor-intensive and isolated machine operations toward connected, data-informed, and increasingly autonomous production. Industry 4.0 concepts such as cyber-physical systems, machine connectivity, enterprise integration, artificial intelligence (AI), and big-data analytics are now discussed not only as future technologies but as practical mechanisms for improving production visibility, quality consistency, responsiveness, and resource utilization. Evidence from the Bangladeshi textile and apparel sector shows growing attention to Industry 4.0 readiness and smart-factory capabilities (Mim et al., 2024), while organizational studies emphasize that successful adoption of AI and big-data analytics depends on the technological, organizational, and managerial readiness of textile and garment firms (Hossain et al., 2024). The modernization of textile production is also closely associated with Internet of Things (IoT) sensing, digital twins, and predictive maintenance. IoT-enabled monitoring can support real-time observation of machine states, process conditions, and resource consumption across production lines (Petrillo et al., 2024). Digital-twin applications extend this logic by coupling physical textile processes with virtual representations that can support optimization and sustainability objectives, including dyeing-process improvement (M. Kim et al., 2024). Predictive-maintenance research further demonstrates how machine-learning and IoT signals can be used to anticipate equipment conditions in industrial and textile settings, reducing unplanned stoppage and supporting maintenance planning (Elkateb et al., 2024). These developments indicate that automation adoption is not a single technology decision; rather, it involves a portfolio of digital, analytical, control, and machine-level capabilities. Quality control and process reliability represent another major application area. Automated inspection using supervised and unsupervised learning can reduce dependence on purely manual visual checking and provide scalable defect-detection support (Ferreira et al., 2024). At the same time, adoption is constrained by cost, infrastructure, skills, organizational resistance, and interoperability challenges, which have been documented in the ready-made garment sector (Salman et al., 2024). Firm characteristics also shape the adoption of AI, robotics, sensors, big data, 3D technologies, and cyber-physical systems in apparel manufacturing (Van Ta et al., 2024). As a result, a meaningful analysis of smart textile production needs to take into account the intensity of the technology as well as the organizational or country-specific context in which the technology adoption takes place. An important methodological challenge is that the existing data, which is open to the public, is dispersed among different surveys, technology classes, activities, countries and years. In this study, a new machine-learning-ready dataset based on modern textile production system has been created by collecting information on technology adoption and digital-readiness open to the public as a solution to that problem. The study then assessed whether it was possible to classify technology-adoption maturity using the traditional machine-learning model and 1D CNN, while maintaining the interpretability of the model through explainable AI. Therefore, the main contribution of this research is not limited to comparing the performance of different models; rather, it presents a structured data-integration and analytical framework, which combines production-function evidence, country context, digital readiness, technology maturity and model explanation into a single reproducible research design.

## 2 LITERATURE REVIEW

### 2.1 Industry 4.0 and Industry 5.0 in Textile and Apparel Production

Recent literature shows that smart-manufacturing research in clothing and textile production has broadened from isolated automation applications to system-level Industry 4.0 integration. A systematic review of Industry 4.0 applications in the clothing sector identifies industrial automation, IoT, cybersecurity, additive manufacturing, digital platforms, and connected production as recurring technological themes (Monteiro et al., 2024). In parallel, the transition toward Industry 5.0 introduces a stronger emphasis on human-centricity, resilience, sustainability, and collaboration between intelligent machines and workers rather than automation for its own sake (Safavi Jahromi & Ghazinoory, 2025). For textile production systems, this shift suggests that adoption maturity should be interpreted as a continuum ranging from manual or mechanized processes to digital and advanced smart-production configurations.

### 2.2 Artificial Intelligence and Autonomous Production Optimization

AI is increasingly used across dyeing, printing, finishing, process control, quality prediction, and recipe optimization. Recent reviews describe deep-learning and AI applications that support color prediction, defect recognition, and automated decision-making in wet processing (Ingle & Jasper, 2025). Beyond prediction, data-driven simulation and autonomous optimization frameworks are being investigated to improve production decisions and validate optimizers under realistic textile-manufacturing conditions (Kins et al., 2025). These studies motivate the use of nonlinear learning models in adoption research because the relationship between digital readiness, production function, country context, and technology maturity may not be adequately represented by simple linear boundaries.

### 2.3 Adoption Barriers and Organizational Readiness

Technology adoption in textile manufacturing is constrained by more than technical feasibility. Research in Indian textile and clothing industries highlights barriers related to investment requirements, organizational readiness,

workforce capabilities, infrastructure, and strategic alignment (Singh et al., 2025) . Structural modelling studies of Industry 4.0 barriers similarly show that the transition to smart manufacturing depends on interacting technical, financial, managerial, and ecosystem-level conditions (Mahmood et al., 2025) . These findings justify including contextual predictors, such as country and digital-readiness indicators, in addition to production-function variables when modelling technology-adoption maturity.

## 2.4 IoT, SCADA, Robotics, and Connected Automation

Connected automation increasingly links textile machines to supervisory and analytical systems. Low-cost IoT-based SCADA architectures have been proposed for centralized monitoring of heterogeneous textile machinery and controllers (Amin et al., 2025) . Robotic automation research also targets unmanned or reduced-labor production through coordinated machine handling, sensing, and process integration (Lee et al., 2025) . Such approaches illustrate the movement from isolated mechanization toward production systems in which equipment, monitoring, data exchange, and automated control operate as a coordinated technological stack.

## 2.5 Smart Quality, Digital Twins, and Intelligent Manufacturing Systems

Quality assurance is one of the most visible entry points for AI in textile manufacturing. Computer vision and machine learning are increasingly applied to textile defect detection, creating automated inspection systems that can complement or replace portions of manual quality control (Ozek et al., 2025) . Digital-twin research in apparel production extends monitoring toward production-line management, optimization, maintenance, and virtual experimentation (Bi et al., 2025) . Intelligent manufacturing interfaces are also emerging at the execution-system level; for example, large-language-model-driven interaction with manufacturing execution systems has been explored for garment manufacturing (Yuan et al., 2025) . Together, these streams show that smart production spans machine-level automation, process intelligence, decision support, and enterprise-level digital integration.

## 2.6 Advanced Garment Automation and Robotic Sewing

Recent work also demonstrates increasingly specialized forms of automation within garment production. Reviews of technological advancements in textile material and machine manufacturing emphasize the growing role of AI, mechatronics, digitization, and intelligent equipment (Amjad & Joshi, 2025) . Deep-transfer-learning approaches have been proposed for sewing-stitch defect detection (Jung et al., 2025) , while autonomous sewing systems combine soft robotic fingers and machine vision to manipulate deformable fabrics (Shen et al., 2025) . Vision-guided robotic gripping has been designed to connect automated fabric handling with cutting and sewing processes (Choi et al., 2025) , and fixture-free dual-arm sewing systems use high-speed edge detection to support autonomous garment operations (Tang et al., 2025) . These advances indicate that cutting, sewing, handling, and inspection are becoming key domains for measuring advanced/smart adoption maturity.

## 2.7 Limitations of Current Research and Research Gap

Despite rapid technological progress, much of the literature remains application-specific. Automated top-stitching and smart retrofitting, for example, demonstrate how legacy garment machines can be upgraded using vision, sensors, and actuators (T. Kim et al., 2025) , but such studies do not necessarily provide a comparable cross-country view of adoption maturity. Sector-wide technology-adoption reviews similarly identify a gap between available innovations and their implementation across the textile industry (Chourasiya & Pandey, 2025) . Existing studies provide rich evidence about different technologies, barriers to technology adoption, and specific use cases. However, the task of creating an integrated dataset by combining technology-acceptance indicators from multiple open sources and then evaluating the technology-maturity classification using both traditional machine learning and deep learning methods is still limited. The present study built an integrated public-source dataset to fill this gap, applied the leakage-aware 70/15/15 evaluation design, compared the performance of four different model families, and interpreted the highest-performing model through global and local explainable AI analysis.

## 2.8 Research Questions

- What adoption patterns are visible across countries, production functions, and technology-maturity levels in the constructed public-source textile dataset?
- How accurately can Random Forest, XGBoost, SVM, and 1D CNN classify technology-adoption maturity in title-aligned textile production observations?
- Which of the four evaluated models provides the strongest reported predictive performance?
- How does the best-performing 1D CNN behave across the Basic/Manual, Intermediate/Mechanized, Digital, and Advanced/Smart classes according to precision, recall, F1-score, confusion matrix, loss, and ROC analysis?
- Which production, country, temporal, and digital-readiness features contribute most strongly to 1D CNN decisions according to Integrated Gradients?

## 2.9 Research Objectives

- To construct a unified, machine-learning-ready dataset from publicly available technology-adoption and digital-readiness sources relevant to textile production.
- To characterize adoption maturity across countries, production functions, domains, and digital-readiness conditions.
- To compare Random Forest, XGBoost, SVM, and 1D CNN under a common 70/15/15 experimental design.
- To evaluate the best-performing 1D CNN using class-wise precision, recall, F1-score, confusion matrix, loss, ROC-AUC, and precision-recall evidence.
- To interpret global and local 1D CNN decisions using Integrated Gradients and identify the most influential smart-production features.

## 3 MATERIALS AND METHODS

### 3.1 Study Area

This study has been conducted in the context of modern textile and apparel production systems, with particular emphasis on the adoption of technology in production planning, fabrication, cutting, sewing, finishing / ironing, quality control, quality management and related digital functions. The integrated dataset covers Bangladesh, Chile, Ethiopia, India and Senegal and contains data for various survey years from 2019 to 2023. As a result, the analytical scope of this research is not limited to any particular factory or plant; rather, it follows a multi-country analytical scope. This has made it possible to compare technology-adoption patterns between different industry environments and digital-readiness contexts.

### 3.2 Study Design

The study used a quantitative secondary-data integration and supervised-learning design. A single analytical dataset has been created by collating clear, consistent, encoded and updated information on technology-adoption open to the public. The main modeling outcome was a four-tier technology-maturity label: 0 = Basic / Manual, 1 = Intermediate / Mechanized, 2 = Digital, and 3 = Advanced / Smart. To keep the predictive experiment consistent with the main objective of the research, modeling has been limited to observations related to core textile production, production operations, and quality management. Only commercial sales and marketing-related records are kept for descriptive analysis of the entire dataset, but they are excluded from the main model experiment.

### 3.3 Sample Size and Selection

**Table 1: Dataset Characteristics and Experimental Context**

| Item                           | Description                                                  | Value                      |
|--------------------------------|--------------------------------------------------------------|----------------------------|
| Dataset                        | Integrated public-source textile technology-adoption dataset | Constructed for this study |
| Full observations              | All cleaned analytic observations                            | 8,198                      |
| Variables                      | ML-ready columns                                             | 26                         |
| Countries                      | Bangladesh, Chile, Ethiopia, India, Senegal                  | 5                          |
| Production functions           | Apparel/production/quality/digital functions                 | 9                          |
| Survey coverage                | Available source years                                       | 2019–2023                  |
| Title-aligned modelling subset | Core Textile + Production Operations + Quality Management    | 5,472                      |
| Train / validation / test      | Group-aware partition                                        | 3,830 / 821 / 821          |
| Target                         | Technology-adoption maturity                                 | 4 classes                  |
| Missing values                 | Final ML-ready file                                          | 0                          |

The full constructed dataset contains 8,198 analytic observations and 26 columns, with no missing values in the finalized modelling file. These observations are source-count-backed analytical records reconstructed from published frequency information and contextual indicators; they should not be interpreted as 8,198 unique firms. Title-aligned filtering retained 5,472 observations for modelling. A group-aware split based on the source grouping variable was used to prevent records originating from the same reconstructed source group from appearing in more than one partition. The

final split contained 3,830 training observations (69.99%), 821 validation observations (15.00%), and 821 test observations (15.00%). The test set comprised 168 Basic/Manual, 517 Intermediate/Mechanized, 13 Digital, and 123 Advanced/Smart observations (Table 1).

### 3.4 Public Data Sources and Dataset Construction

The dataset was created by integrating publicly available technology-adoption and digital-readiness evidence rather than by generating synthetic feature values. The technology-adoption component was grounded primarily in the World Bank Firm Adoption of Technology (FAT) framework and related establishment-level technology-sophistication evidence (Comin et al., 2025), together with work examining how technology is distributed within and across firms (Cirera et al., n.d.). Country-level digital context was aligned with established ICT and digitalization indicators, consistent with prior work on digitalization and resilience (Abidi et al., 2023) and on mobile broadband and internet bandwidth as development-related digital infrastructure measures (Bala, 2024). Manufacturing and productivity context was also considered in relation to cross-country evidence on jobs and productivity in global value chains (Pahl et al., n.d.). During cleaning, descriptive URLs, notes, and non-modelling metadata were removed from the ML-ready file, while country, production-function, domain, year, internet-penetration, and textile-specific indicators were retained. The final file was therefore structured for direct use in machine-learning experiments.

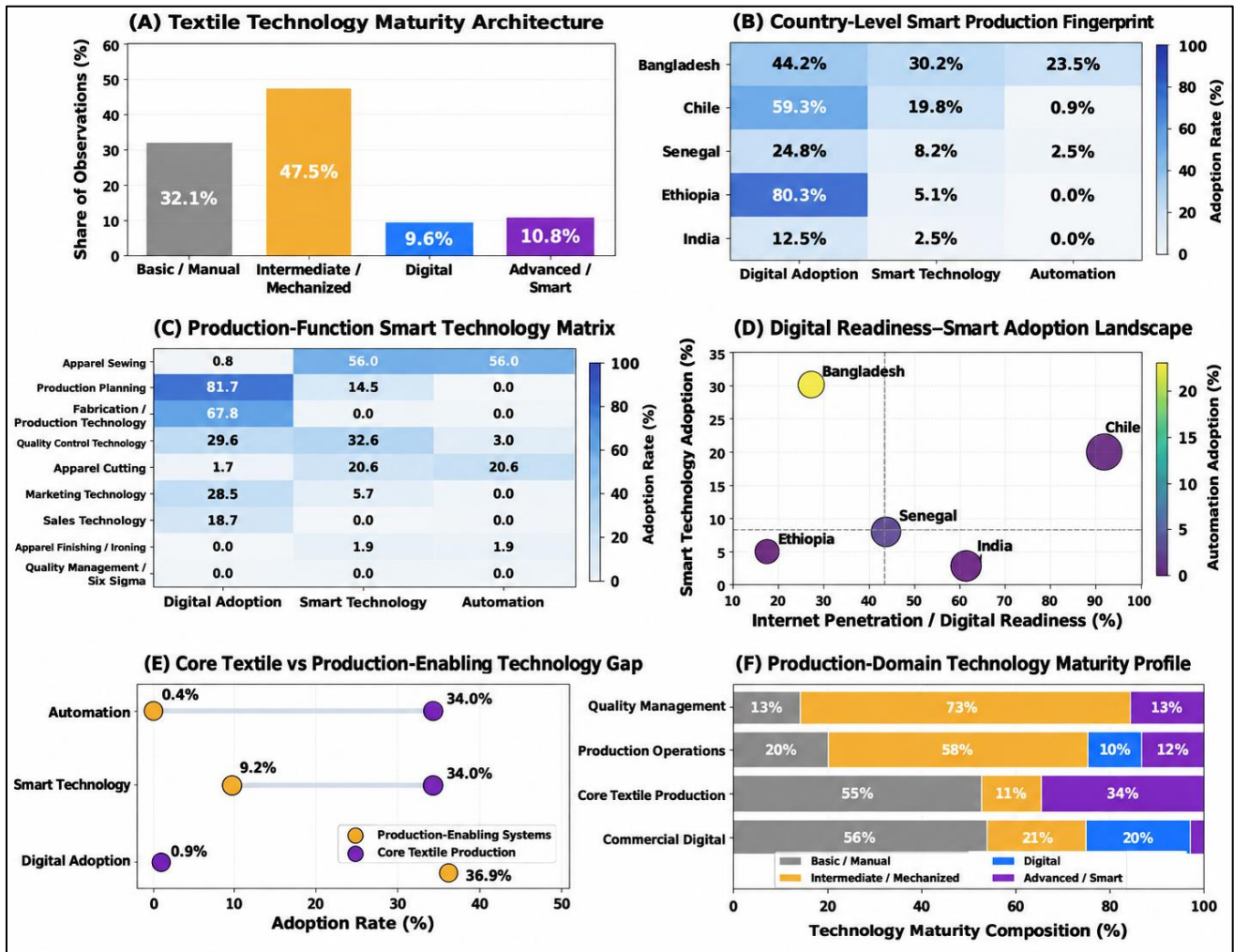


Figure 1: Multidimensional Analytical Overview of the Constructed Textile Technology Adoption Dataset

Figure 1 summarizes the full dataset in six complementary panels. Panel (A) shows that Intermediate/Mechanized observations form the largest maturity group (47.5%), followed by Basic/Manual (32.1%), Advanced/Smart (10.8%), and Digital (9.6%). Panel (B) highlights strong cross-country heterogeneity: Bangladesh shows comparatively high smart-technology and automation shares, while Chile and Ethiopia show higher digital-adoption shares but lower automation. Panel (C) demonstrates substantial variation across production functions, with apparel sewing, production planning, fabrication/production technology, and quality control exhibiting distinct adoption profiles. Panel (D) compares internet penetration with smart-technology adoption and reveals that higher digital readiness does not translate uniformly into higher automation. Panel (E) contrasts core textile functions with production-enabling systems, showing different adoption patterns across digital, smart, and automation dimensions. Panel (F) further shows that

technology maturity varies by production domain, confirming that the dataset contains meaningful structural differences rather than a single uniform adoption pattern.

### 3.5 Measures and Variables

The target variable was target\_tier\_code, representing the four technology-maturity classes. All other target-prefixed variables and the cross-validation group identifier were excluded from the predictor set to avoid target leakage. After title-aligned filtering and removal of zero-variance variables, the model input contained 18 numeric predictors. These included survey year, internet penetration, textile-specific status, country indicators, production-function indicators, and production-domain indicators. Standardization was applied for SVM and 1D CNN models, while tree-based models were trained on the numeric feature matrix without requiring scale normalization.

### 3.6 Research Tools and Techniques

This analysis is carried out using Python. Pandas and NumPy for data preparation, Random Forest, SVM, scikit-learn for preprocessing and evaluation, XGBoost for gradient-boosted decision tree, and PyTorch for 1D CNN implementation. The Random Forest model uses an ensemble of multiple decision trees with class-aware weighting. Multiclass probability objective and regularized tree boosting have been implemented in the XGBoost model. The SVM model uses radial basis function (RBF) kernel with standardized predictor. In the 1D CNN model, the feature vector is treated as a one-dimensional signal. The model architecture uses three convolutional stages with 32, 64 and 96 channels. In addition to this, batch normalization, ReLU activation, max pooling, dropout, adaptive average pooling, 64-unit fully connected layer and an output layer for four classes have been included. AdamW optimizer for model training, class-weighted cross-entropy loss, reduction in learning rate when validation performance is stable, 128 batch size and 50 epochs have been used. The best model checkpoint has been selected based on the validation performance.

### 3.7 Data Analysis Techniques

Model performance was evaluated using overall accuracy, class-wise precision, recall, F1-score, confusion matrix analysis, training-validation loss, receiver-operating-characteristic (ROC) analysis, and precision-recall evidence. The finalized model comparison used the reported test accuracies supplied for this study. Because the four classes are imbalanced-particularly the Digital class-the class-wise classification report was emphasized in addition to overall accuracy. Explainable AI was performed using Integrated Gradients. Global attribution aggregated absolute feature contributions across test observations, while local attribution examined the signed contributions for an individual prediction. XAI values were interpreted as model-attribution evidence rather than causal effects.

## 4 RESULTS AND ANALYSIS

### 4.1 Multidimensional Dataset Analysis

The descriptive analysis of Figure 1 shows that the built-in dataset contains multiple layers of textile technology maturity; that is, the dataset is not dominated by a single advanced-technology category. The highest share is Intermediate / Mechanized class, which amounts to 47.5%. This indicates that the transition from traditional machine-based production systems to digitally connected and intelligent production is not yet complete in the various contexts presented. Among the complete dataset, Advanced / Smart monitoring rate is 10.8%, and Digital monitoring rate is 9.6%. Country and function-based panels show that technology adoption is highly uneven. Digitalization, smart technology and automation do not move at the same speed, and the relative position of a country also changes depending on which adoption dimension is being analyzed. This diversity indicates that it is more appropriate to use a multivariate model rather than relying solely on a descriptive index.

### 4.2 Machine-Learning Model Performance

**Table 2: Performance Comparison of Technology-Adoption Models**

| Model         | Reported Accuracy | Performance Rank |
|---------------|-------------------|------------------|
| Random Forest | 92.00%            | 4                |
| XGBoost       | 93.00%            | 3                |
| SVM           | 93.56%            | 2                |
| 1D CNN        | 96.10%            | 1 (Proposed)     |

Four supervised models were evaluated on the common experimental task. Table 2 summarizes the finalized reported test accuracies. The 1D CNN achieved the highest accuracy at 96.10%, followed by SVM at 93.56%, XGBoost at 93.00%,

and Random Forest at 92.00%. The difference indicates that the convolutional model provided the strongest reported separation of technology-maturity classes in the prepared feature space.

The remaining detailed analysis therefore focuses on the 1D CNN as the best-performing model. Accuracy is not interpreted alone; class-specific precision and recall, the confusion matrix, loss behavior, ROC discrimination, and XAI are used to examine where the model performs strongly and where uncertainty remains.

#### 4.3 1D CNN Classification Report

Table 3 presents the 1D CNN classification report for the 821-observation test set. Basic/Manual, Intermediate/Mechanized, and Advanced/Smart classes all achieved F1-scores above 95%. The Digital class achieved high recall (92.31%) but substantially lower precision (54.55%), indicating that most true Digital observations were recovered but some observations from other maturity levels were also assigned to the Digital class. This behavior is consistent with the very small Digital test support of 13 observations and should be interpreted cautiously.

**Table 3: 1D CNN Classification Report on the Test Set**

| Class                     | Precision | Recall | F1-Score | Support |
|---------------------------|-----------|--------|----------|---------|
| Basic / Manual            | 94.19%    | 96.43% | 95.29%   | 168     |
| Intermediate / Mechanized | 99.20%    | 95.94% | 97.54%   | 517     |
| Digital                   | 54.55%    | 92.31% | 68.57%   | 13      |
| Advanced / Smart          | 93.70%    | 96.75% | 95.20%   | 123     |
| Accuracy                  |           |        | 96.10%   | 821     |

The weighted precision, recall, and F1-score were 96.64%, 96.10%, and 96.27%, respectively. The macro F1-score was lower at 89.15% because it gives equal weight to the small Digital class, demonstrating why class-level reporting is essential even when overall accuracy is high.

#### 4.4 1D CNN Training and Validation Loss

The training and validation loss trajectory is shown in Figure 2. The supplied training trace spans 50 epochs and marks epoch 48 as the selected best checkpoint. Training loss declines over the course of optimization, while validation loss stabilizes at a lower level after the early epochs. The absence of a sustained late-stage rise in validation loss suggests that the selected checkpoint avoided a clear overfitting collapse within the reported experiment.

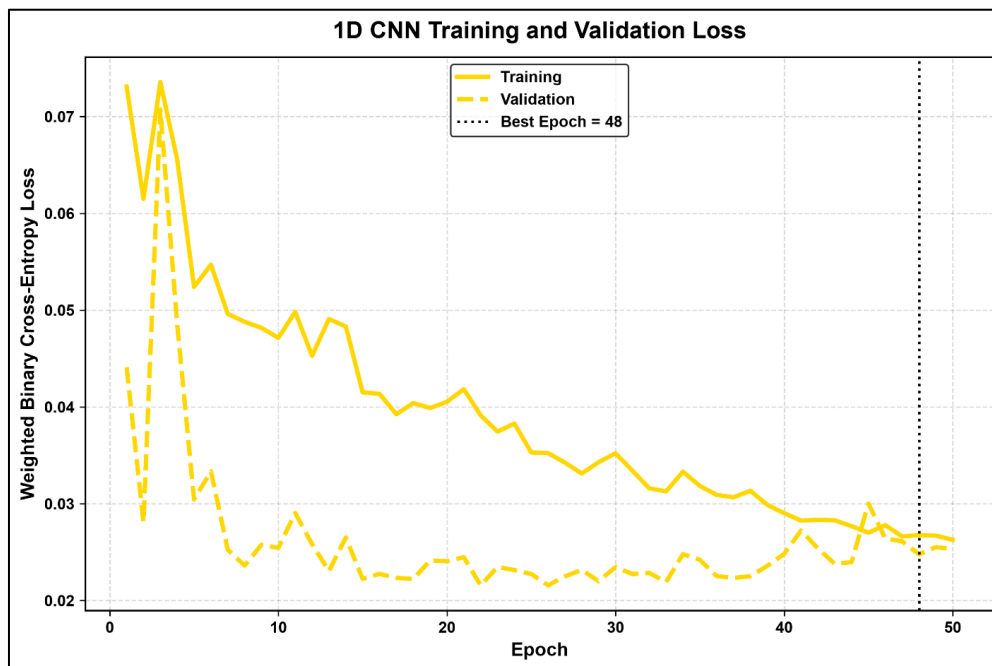


**Figure 2: 1D CNN Training and Validation Loss for Technology-Adoption Classification**

#### 4.5 1D CNN Confusion Matrix Analysis

Figure 3 presents the four-class confusion matrix corresponding to the reported 96.10% accuracy. The diagonal contains 162 correctly classified Basic/Manual observations, 496 Intermediate/Mechanized observations, 12 Digital observations, and 119 Advanced/Smart observations. The largest off-diagonal errors occur around the Intermediate/Mechanized class, reflecting its dominant support and its proximity to neighboring maturity levels.

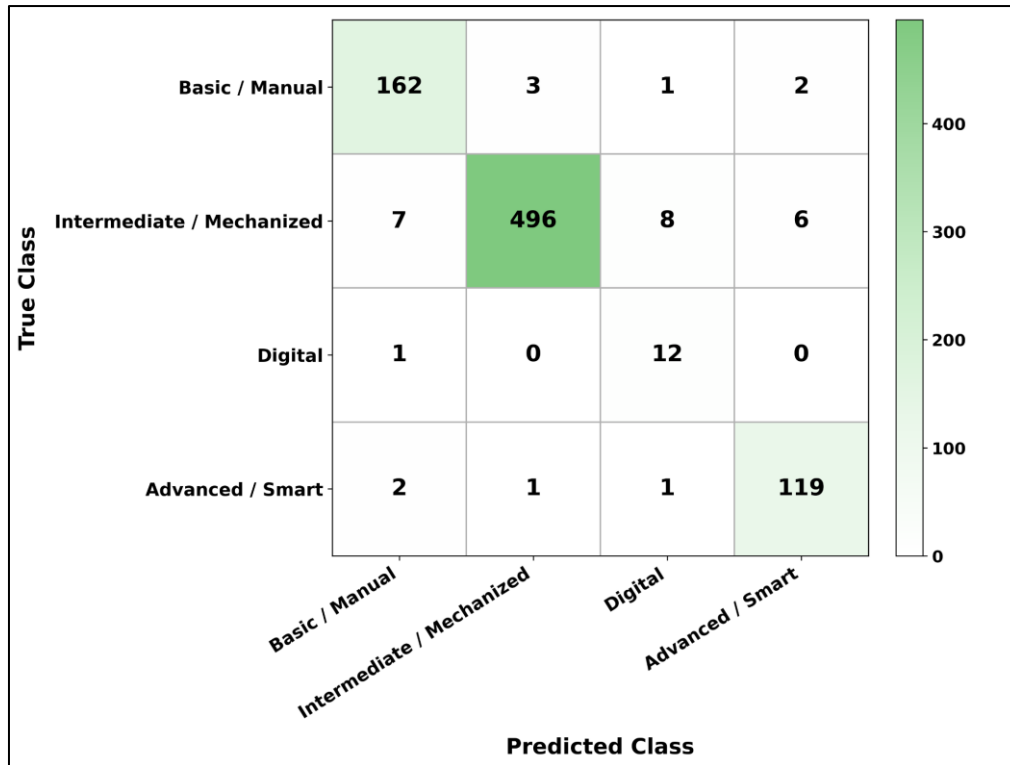


**Figure 3: 1D CNN Confusion Matrix for Technology-Adoption Maturity Classification**

The confusion matrix supports the class-level report: Advanced/Smart and Basic/Manual observations are separated reliably, while the Digital category is recovered with high recall despite its limited support. Because only 13 Digital cases occur in the test set, additional validation with larger samples is required before treating the Digital-class precision estimate as stable.

#### 4.6 1D CNN ROC and Precision-Recall Analysis

Figure 4 shows the ROC curve provided by 1D CNN and reports the AUC value as 0.998094. At most thresholds, the curve is located near the upper-left region, indicating strong ranking discrimination of the model in the reported ROC analysis. Since there are four technology-maturity classes in the original classification problem, the ROC result should be interpreted not as a substitute for the multiclass confusion matrix and class-wise performance metric, but as a supplementary discrimination summary. The precision-recall behavior in this manuscript is represented by the class-specific precision and recall value given in Table 3. No final PR-AUC value was provided individually; therefore, it was not inferred or artificially determined in this study.

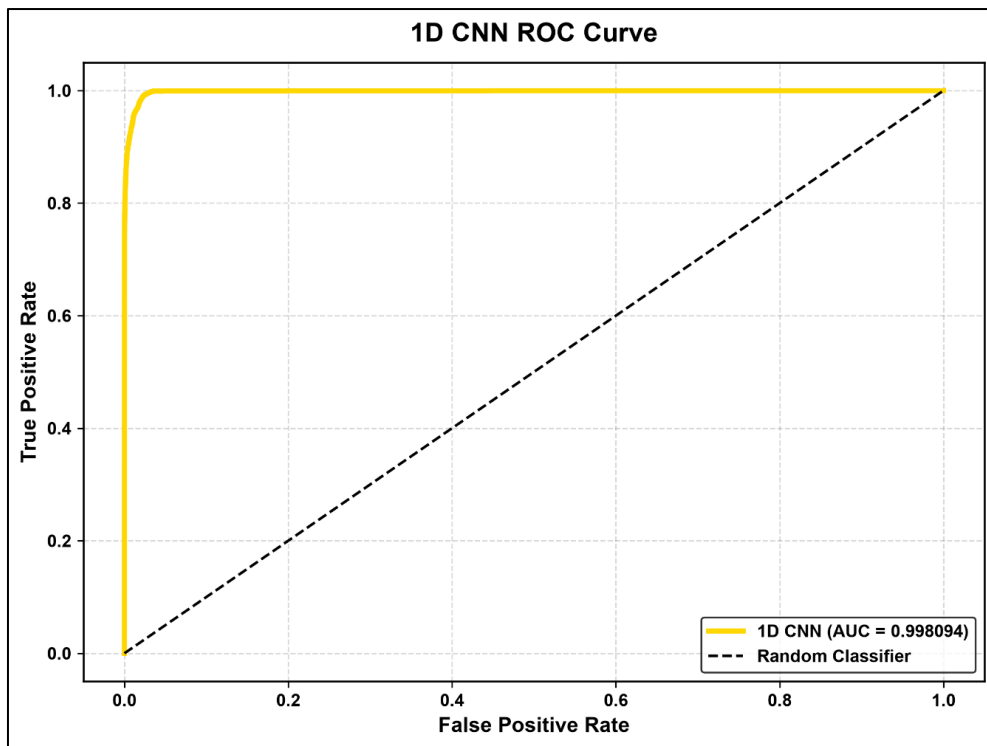


**Figure 4: 1D CNN ROC Curve for Technology-Adoption Discrimination**

#### 4.7 1D CNN Global XAI: Integrated Gradients Analysis

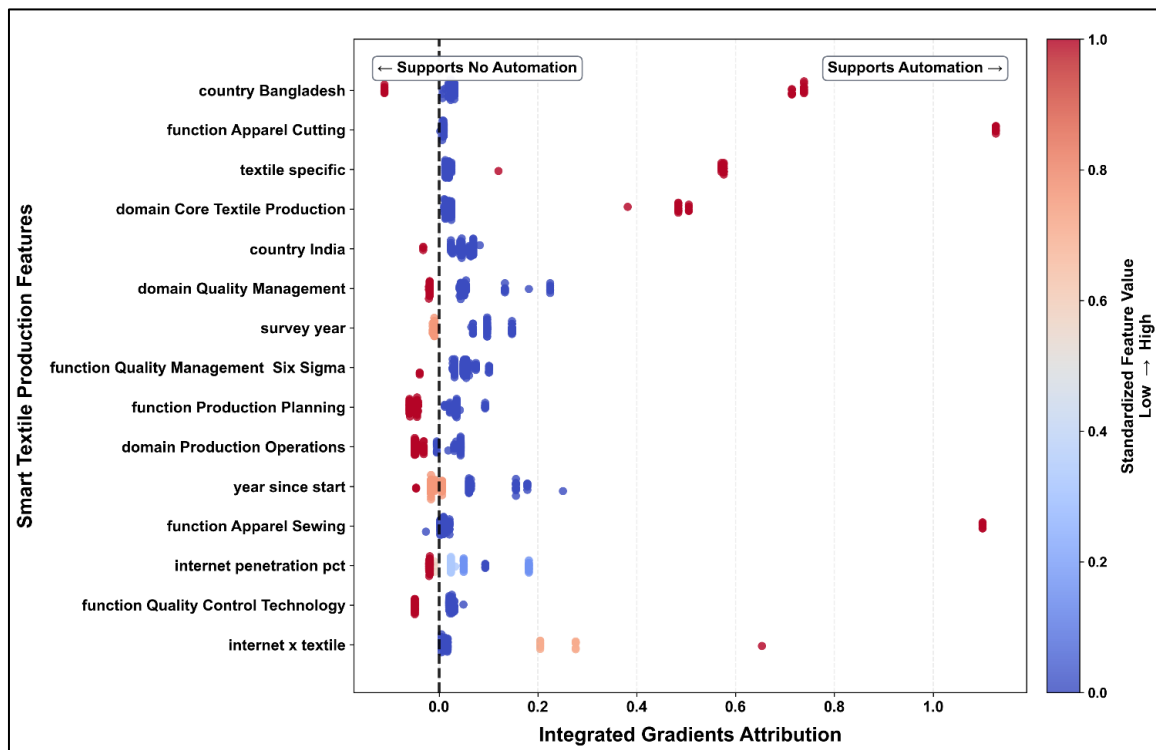


**Figure 5: 1D CNN Global XAI: Integrated Gradients Analysis**

Global Integrated Gradients analysis is presented in Figure 5. The most powerful attributions include Bangladesh country context, Apparel Cutting, Textile-specific indicator, Core Textile Production, India country context, Quality Management, Survey year, Six Sigma / quality-management function, Production Planning, Production Operations, Apparel Sewing, Internet penetration and Interaction between internet penetration and textile status. The positive attributions on the right side of the plot support the automation / smart-technology direction, while the negative attributions point to the relatively lower-adoption direction. The results suggest that the model makes decisions using

the combined effects of production-function structure, national context, and digital-readiness variables, rather than relying on a single predictor.

These attributions are considered to be explanatory signals for the fitted model and should not be interpreted as causal estimates. For example, a country indicator may contain information on the composition of underlying public data, survey timing, industrial structure, and technology availability. As a result, the main use of XAI output is to identify which dimensions require more in-depth substantive interpretation and additional external validation.

#### 4.8 1D CNN Local XAI for a Test Sample

Figure 6 shows the local Integrated Gradients explanation for an observation in the test set, where the observation is predicted as a digital class. The biggest positive contribution to this local explanation has come from Production Operations, Chile indicator, Production Planning and Internet penetration. In addition, Quality Management and India Indicator have made relatively small positive contributions. On the other hand, Core Textile Production, Senegal, Bangladesh and fabrication-related indicators contributed in the opposite direction. This local explanation shows that the same model can generate predictions for a particular observation by combining contextual and process-specific features differently than in a global summary.

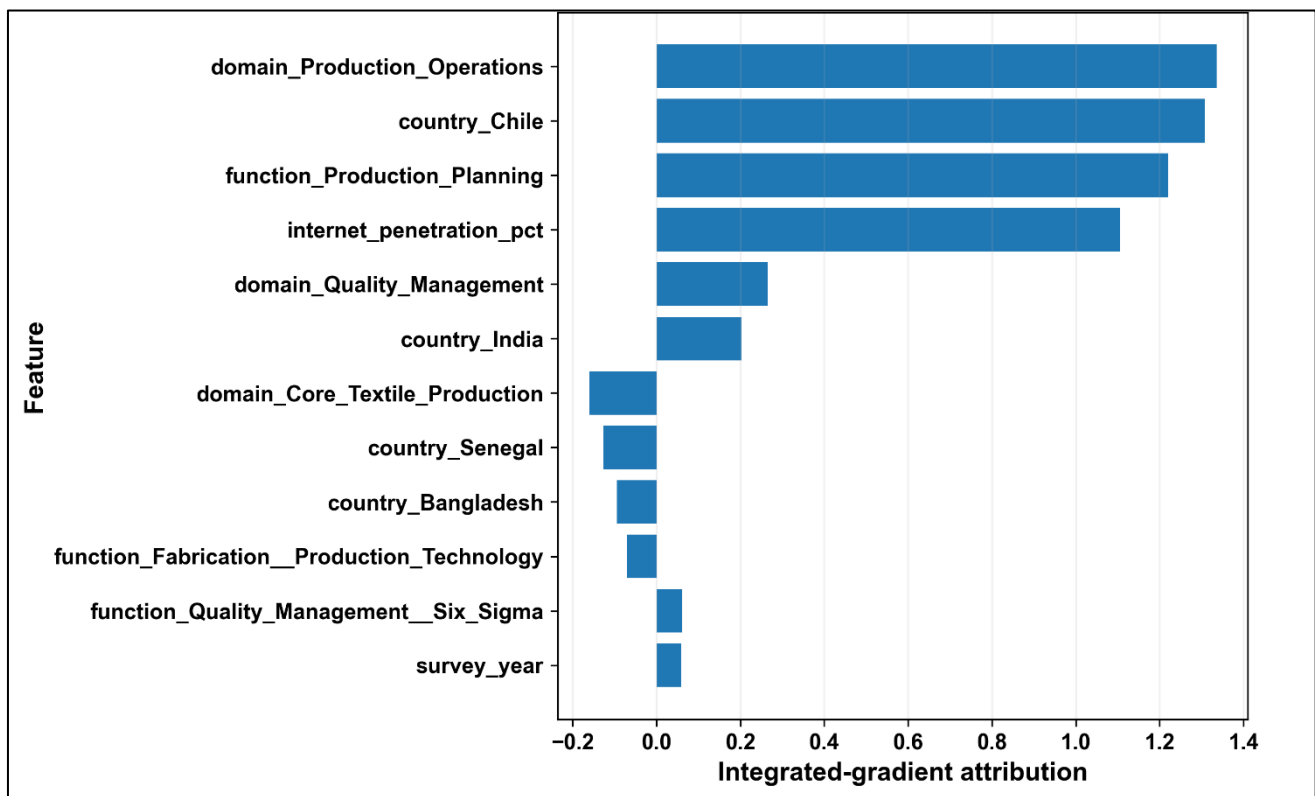


Figure 6: 1D CNN Local XAI for a Test Sample Predicted as Digital

## 5 DISCUSSION

The results show that the built-in dataset effectively represents the different levels of technology adoption in modern textile production systems. The predominance of the intermediate / mechanized class indicates that many observations are still in the intermediate stage between conventional manual production and fully smart manufacturing. These findings are consistent with apparel industry-related research in Bangladesh, where technology adoption is influenced by organizational capability, perceived benefits, investment constraints, and implementation conditions. (Iqbal & Su, 2026) .Similarly, the differences in adoption patterns between different countries and production functions represent the textile digital transformation as a heterogeneous process. Of the four models, 1D CNN achieved the highest accuracy of 96.10 percent, indicating the ability to detect nonlinear relationships between production-related and contextual indicators. However, there were only 13 test observations in the digital class and its precision was relatively low. This indicates a possible overlap between class imbalance and intermediate digitalization and advanced smart-production configuration. Previous studies on Industry 4.0 adoption have also noted the uneven integration of different technologies and organizational capabilities (Islam et al., 2026) . ROC and XAI analysis shows that internet penetration, production planning, core textile function, quality-management indicator and apparel operation model play an important role in decision making. These results are consistent with the development of smart textile manufacturing

through IoT, digital twin and real-time production integration (De Felice et al., 2026; Fareed et al., 2026). Systematically, the study demonstrates the effectiveness of combining disaggregated public technology-adoption data into a unified analytical framework. However, class imbalance, source harmonization, representativeness, and the need for external validation in independent textile-firm datasets remain important limitations.

### 5.1 Findings

1. The constructed dataset contains 8,198 analytic observations, 26 variables, five countries, nine production functions, and survey coverage from 2019 to 2023.
2. The full dataset is dominated by Intermediate/Mechanized observations (47.5%), while Advanced/Smart and Digital observations account for smaller shares of 10.8% and 9.6%, respectively.
3. The title-aligned modelling subset contains 5,472 observations and was divided into 3,830 training, 821 validation, and 821 test observations using a group-aware 70/15/15 design.
4. The reported accuracies were 92.00% for Random Forest, 93.00% for XGBoost, 93.56% for SVM, and 96.10% for 1D CNN, making the 1D CNN the best-performing model.
5. The 1D CNN achieved weighted precision of 96.64%, weighted recall of 96.10%, and weighted F1-score of 96.27% on the reported test set.

### 5.2 Recommendations

1. Future studies should validate the integrated dataset and the 1D CNN on independent firm-level textile or apparel microdata before operational generalization.
2. The Digital class should be expanded through additional public sources or primary data collection because its small test support reduces the stability of precision estimates.
3. Model assessment should continue to report class-wise precision, recall, F1-score, confusion matrices, ROC/PR evidence, and XAI rather than relying on accuracy alone.
4. Technology-adoption studies should retain production-function information so that automation in cutting, sewing, quality control, and production planning can be analyzed separately.
5. Integrated Gradients and other explanation methods should be used as model-audit tools, while causal interpretations should be reserved for designs that explicitly identify causal effects.

### 5.3 Limitations

1. The study used data from only five countries, so the results may not be directly applicable to the textile industry in all countries.
2. Since the dataset is generated from different public sources, there are some differences between the data collection method, survey year and technology definition.
3. The models have not yet been externally validated in the independent real-world textile company dataset, so validation with more new and firm-level data is needed in the future.

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## 6 CONCLUSION

This study presents a data-integration and machine-learning framework for analyzing the adoption of automation and smart technology in modern textile production systems. A new ML-ready dataset has been created using information on technology-adoption and digital-readiness open to the public, with a total of 8,198 analytical observations from five countries and nine production functions. Descriptive analysis shows that the picture of technology adoption is diverse; intermediate / mechanized production is still dominant and advanced / smart adoption is unevenly spread across different countries and functions. Four models were compared using a group-aware 70/15/15 experimental design on a production-focused subset of the study. According to the final results, 1D CNN achieved a maximum accuracy of 96.10%, which is better than SVM, XGBoost and Random Forest. The Detailed Classification report showed that the model provided strong performance in Basic / Manual, Intermediate / Mechanized and Advanced / Smart classes, but a relatively small digital class was the main source of uncertainty in terms of precision. AUC 0.998094 was found in the ROC analysis. Integrated Gradients-based XAI analysis shows that at both global and local levels, production function, country context, quality management, survey timing and digital readiness play an important role in model decisions. Overall, the study shows that it is possible to effectively analyze textile technology adoption by organizing technology-adoption data held in isolation in different public sources into an integrated analytical framework. The study also highlights the need for greater firm-level validation samples, improved maturity class balance, and more transparent and explainable evaluation in the future.

## STATEMENTS ON COMPLIANCE WITH ETHICAL STANDARDS

### *Disclosure of conflict of interest*

The authors declare no conflicts of interest regarding this manuscript.

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