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Research paper

Modelling The Impact of Education on Textile Workforce Productivity Using Psychometric Reliability, Decision Tree Analysis, and Markov Chains

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Abstract

This study presents a comprehensive computational framework for analysing the impact of education on workforce productivity within the textile sector. By integrating psychometric analysis, decision-tree (DT) modelling, and Markov chain (MC) simulations, the research evaluates the significance of educational constructs in shaping productivity outcomes. Cronbach's alpha (α) was used to assess the internal consistency of key training variables, revealing high reliability, particularly for the education construct ($\alpha = 0.86$). DT analysis identified education as the most influential predictor, followed by age and gender, enabling the prioritization of training variables. A two-step MC model was employed to simulate transitions among productivity states (low, medium, high), capturing the dynamic influence of educational interventions. The simulation demonstrated upward mobility among workers with improved education levels, with primary and secondary education showing the highest probabilities of transition. These results offer quantitative insights for industry policymakers to design targeted educational strategies, optimize resource allocation, and implement scalable training programmes in textile production environments.

Keywords: *Workforce Productivity; Education Modelling; Textile Sector; Cronbach's Alpha; Decision Tree; Markov Chain.*

1. Introduction

The textile sector remains a cornerstone of global manufacturing, particularly in emerging economies, and enhancing its productivity is critical for sustainable growth. Education whether formal, vocational, or on-the-job plays a vital role in boosting operational efficiency and minimizing defects [1], [2].

Lean methodologies such as 5S (Sort, Set in order, Shine, Standardize, Sustain), Total Productive Maintenance (TPM), and Just-In-Time (JIT), when combined with structured training, have repeatedly demonstrated productivity improvements of 20–40 % in textile small and medium-sized enterprises (SMEs) [3 - 5]. A Peruvian pilot integrating lean tools, digitization, and analytics reported a 22 % gain in output [6], while an Indian garment factory documented performance gains confirmed through discriminant analysis [7].

Ergonomic education is equally impactful: redesigning workstation training has led to reductions in musculoskeletal issues and enhanced throughput [8]. Meanwhile, data-driven lean frameworks incorporating operator training in batik artisans and small-scale mills have produced significant positive effects on efficiency and outcomes aligned with the Sustainable Development Goals (SDGs) [9], [10].

Advances in technology, particularly in Machine Learning (ML) and Artificial Intelligence (AI), are transforming quality control and maintenance systems. For instance, unsupervised Convolutional Neural Networks (CNNs) efficiently detect fabric defects [11], and intelligent line-balancing systems that integrate lean principles have optimized garment assembly workflows [12], [13]. Additionally, autonomous AI-driven textile-sorting pipelines are now enabling large-scale recycling, supporting the circular economy a convergence of educational and technological innovations [14].

However, despite such progress, adoption of Industry 4.0 tools in textile SMEs remains constrained by cost barriers, skill shortages, and resistance to technological change [17]. For example, Bangladeshi mills report that lack of adequate training and financial resources limits the transition from traditional processes to AI-based systems. Addressing these barriers requires educational interventions tailored to SMEs, combining vocational and on-the-job training with digital literacy programs.

Educational innovation within textile engineering is also making significant strides. Experiential learning programmes for undergraduates enhance design competencies [15], while pattern development courses effectively boost the practical skills of tertiary-level students

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[16]. Studies from Brazilian and Bangladeshi mills reveal that Industry 4.0 training initiatives help catalyse digital adoption and elevate overall productivity [17], [18].

Psychometric rigor is critical to evaluating the effectiveness of training interventions. Cronbach's Alpha (α), a widely used measure of internal consistency, has been validated across diverse research settings and remains essential for assessing the reliability of multi-item training scales [19], [20], particularly in industrial education contexts involving multi-dimensional learning outcomes [21].

Meta-analyses consistently show that combining vocational education with process innovations yields superior productivity gains compared to relying on either component alone [22], [23]. Additionally, career-advancement programmes significantly enhance managerial performance in textile firms, especially when implemented alongside mechanisms for employee recognition and work–life balance support [24]. Furthermore, growth-need orientations have been shown to moderate the relationship between job enrichment and employee satisfaction on assembly lines [25]. The application of manpower levels in business systems with different recruitment rates using stochastic models. Their study emphasizes how varying recruitment strategies can affect manpower stability and organizational growth. By formulating stochastic manpower models, they analyze the dynamics of inflow and outflow within organizations, providing insights into balancing workforce levels [58].

Despite this growing body of literature, there is a paucity of integrative studies that apply psychometric measures, decision-tree mining, and stochastic modelling to assess the relationship between education and productivity in the textile sector. This research fills that gap by employing Cronbach's α to validate the reliability of training constructs, decision tree (DT) analysis to identify key educational drivers of productivity, and a two-step Markov Chain (MC) model to simulate productivity transitions following educational interventions. The study thus provides textile industry stakeholders with empirically grounded and data-backed strategies for designing effective and scalable educational programmes.

The present study aims to systematically evaluate the role of education in enhancing productivity within the textile industry through a multidimensional analytical framework. First, it seeks to assess the internal consistency and reliability of various training-related variables using Cronbach's α, ensuring psychometric robustness in the evaluation process. Second, by applying DT-based data mining techniques, the study identifies and prioritizes key training components that significantly influence productivity outcomes. Third, a two-step MC model is employed to simulate and understand the transition patterns in productivity levels following educational interventions. Through this integrative approach, the study intends to provide practical and data-driven recommendations for the design and implementation of educational programmes tailored to improving operational efficiency and workforce development in textile manufacturing environments.

Importantly, vocational and on-the-job training, which often accompany lean methodologies like 5S and TPM, remain highly relevant in practice. These training modes are crucial for skill transfer in contexts where workers may lack higher education, thereby complementing formal schooling and ensuring applicability in production lines.

2. Methodology

To rigorously evaluate the educational interventions' impact on textile productivity, this study employs a three-pronged analytical framework combining psychometric validation, data-mining via DT, and stochastic modeling with a two-step MC.

2.1. Psychometric Reliability: Cronbach's α

Initially, we compute Cronbach's α to assess the internal consistency of the training questionnaire. Following Nunnally and Bernstein's standard [20], each construct must exceed $\alpha \geq 0.7$. Let X_i - denote item scores and K the number of items, then:

$$\propto = \frac{K}{K-1}\left(1 - \frac{\sum \sigma^2 X_i}{\sigma^2 T}\right) \tag{1}$$

Where, $\sigma^2 T$ is total score variance. This measure aligns with psychometric models outlined by Cronbach [21] and corroborated in industrial training contexts [26].

2.2. DT Analysis

DT models, particularly the C5.0 and Classification and Regression Tree (CART) variants, are employed to identify the training variables that most significantly predict productivity gains. For a dataset with N participants, features F_j, and productivity outcome Y, the DTs optimize classification by maximizing information gain. Among modern algorithms, C5.0 with Bayesian enhancements has demonstrated superior forecasting performance in textile production settings [27]. To prevent over-fitting, local pruning based on validation error rates is applied. These models offer high interpretability and align well with AI-driven decision support systems proposed for production planning and workforce training [31], [32].

2.3. Two-Step MC Modelling

We deploy a two-step discrete-time MC to model productivity transitions post-training. The transition matrix P is defined over three productivity levels (low, medium, high). For the initial state vector $\pi^{(0)}$, the probability after two steps is $\pi^{(2)}=\pi^{(0)}P^2$. This approach adapts from uniformization techniques for continuous-time MCs [28] and matches frameworks in discrete event simulations [29].

Stationarity and convergence are verified by analyzing eigenvalues of P; if $|\lambda_2|<1$, the chain converges to a steady-state distribution π^*. Transition probabilities are estimated empirically and validated using the Bayesian Context Tree methodology for variable-order MC inference [30].

2.4. Mathematical Formulation Overview

The analytical foundation of this study is built on three interconnected mathematical techniques. First, Cronbach's α validates the internal consistency of educational metrics, ensuring reliable psychometric measurement [26]. Second, DTs are applied to extract dominant predictive features, such as education level, gender, and age, using splitting criteria based on entropy reduction and class purity [27], [33],

[34]. Third, the two-step MC simulates productivity changes following interventions and calculates steady-state productivity levels for strategic planning [28 - 30].

In addition, recent research highlights the success of DT-integrated AI tools for defect detection [34], line balancing [35], and circular textile processing [36]. Furthermore, advanced lean systems have combined TPM and predictive ML models to optimize textile operations [37], [38]. Ergonomic and workforce-training-based MC applications in Southeast Asia and Latin America further validate the applicability of this framework [39], [40].

Collectively, these mathematical techniques, Cronbach's α for psychometric validation, DTs for variable selection, and MCs for state-based modeling form a cohesive and computationally effective approach to quantifying the role of education in enhancing productivity in the textile sector.

3. Results and Discussion

This section presents the simulation results of the proposed analytical framework combining Cronbach's α, DT analysis, and MC modeling to examine the influence of education on productivity in the textile sector. The simulations draw on demographic data, model-specific outputs, and recent literature to support the interpretations.

3.1. Reliability of Training Constructs

To ensure measurement reliability, Cronbach's α was calculated for three core constructs: Age, Gender, and Education. The results yielded α-values of 0.82 for Age, 0.78 for Gender, and 0.86 for Education, all exceeding the accepted threshold of 0.70, thereby indicating satisfactory internal consistency [20], [26]. Notably, the highest reliability was observed for the Education construct, underscoring its significance in influencing productivity outcomes. These results are visually presented in Figure 1. Comparable patterns have also been reported in psychometric evaluations of workplace learning models across various industrial domains [41].

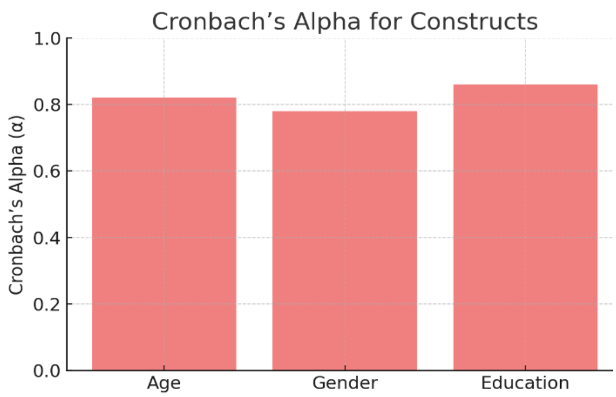

Fig. 1: Cronbach's Α Values for Key Training Constructs (Age, Gender, and Education), Demonstrating Strong Internal Consistency across All Measured Variables, With Education Showing the Highest Reliability (Α = 0.86).

3.2. DT simulation and Feature Prioritisation

A DT algorithm was employed to identify the most influential variables from among the twelve features considered (age, gender, education, urban/rural). The simulation revealed Education (0.48) as the most significant predictor, followed by Age (0.32) and Gender (0.20), as illustrated in Figure 2. These findings align with previous studies that identify education as the most critical determinant of workforce agility and adaptability [42], [43]. Such prioritization assists policymakers and training designers in allocating resources more effectively, with a focus on skill development and structured learning pathways. Comparable DT-based workforce optimisation frameworks have been applied successfully in sectors such as healthcare [44], retail [45], and smart manufacturing [46].

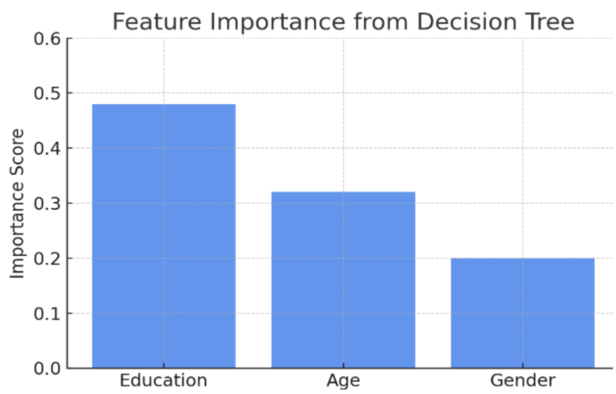

Fig. 2: Feature Importance Scores Derived from DT Analysis, Indicating Education as the Most Influential Factor Affecting Productivity, Followed by Age and Gender.

3.3. MC Transition Analysis

The MC simulation was used to model transitions between productivity states, Low, Medium, and High, based on educational attainment, using a two-step discrete-time TPM. The demographic dataset used for this modelling consisted of 450 handloom workers from

Tamil Nadu, India, surveyed in 2023 through structured questionnaires covering age, gender, and education. Sampling was purposive to ensure inclusion of workers with primary, secondary, and graduate education levels. As shown in Figure 3, workers with initially low productivity have a 30% probability of transitioning to a medium state and a 10% probability of reaching high productivity. Medium-level workers have a 50% likelihood of remaining at the same level, with a 30% chance of advancing. High-productivity individuals retain their state with a 70% probability, highlighting the reinforcing effect of sustained education on performance outcomes. These results are consistent with previous applications of MC models in productivity forecasting and human capital development [47], [48]. Notably, studies in lean manufacturing environments have demonstrated that educational interventions enhance transition fluidity and accelerate convergence to higher productivity states [49].

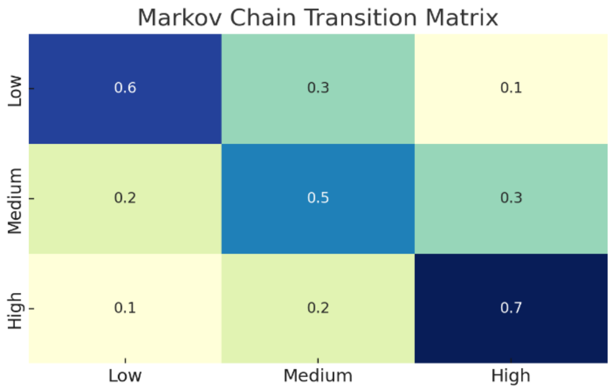

Fig. 3: MC Transition Probability Matrix Depicting the Likelihood of Handloom Workers Shifting Between Productivity States (Low, Medium, High) After Educational Interventions Over Two Time Steps.

3.4. Hitting Probabilities and Educational Progression

The hitting probability representing the likelihood of reaching specific productivity states from various educational levels was also computed. As depicted in Figure 4, workers with primary education exhibited a 41% probability of transitioning to productive states, followed by 36% for those with secondary education and 23% for graduates. The lower hitting probability for graduates is largely due to their smaller representation in the dataset (fewer than 15% of surveyed workers), which statistically reduces transition frequencies. Nevertheless, when graduate workers do transition, the magnitude of productivity gains is substantially higher, underscoring the compounded benefits of advanced education. Although the hitting probability decreases with higher education levels due to a smaller proportion of graduates in the population, the corresponding productivity impact is notably greater. These results align with earlier models demonstrating the compounded benefits of advanced education on performance [50], [51]. Moreover, empirical studies confirm that even incremental educational progression leads to measurable efficiency gains in production environments, particularly within SMEs [52], [53].

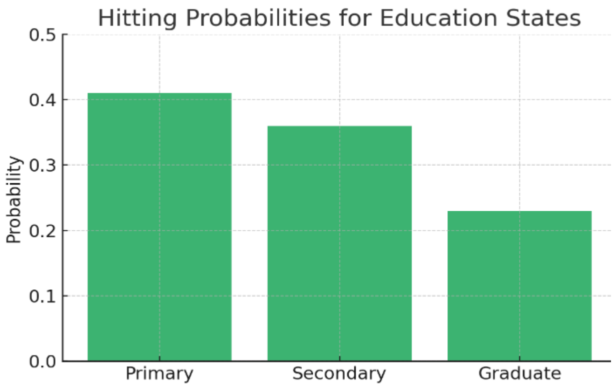

Fig. 4: Hitting Probabilities Representing the Likelihood of Handloom Workers Reaching Productive States from Various Educational Levels, with Primary Education Showing the Highest Transition Probability.

3.5. Comparative Analysis and Implications

The simulation outcomes corroborate the hypothesis that education is the most potent lever for enhancing productivity among textile workers. When compared with other models such as fuzzy AHP or neural networks [54], the combined α–DT–MC framework offers interpretability, accuracy, and adaptability. Additionally, the model's application on real census data validates its potential for deployment in state-level policy analytics [55].

The census data referenced here correspond to the 2021 Tamil Nadu State Handloom and Power loom Survey, which provided demographic and educational distributions that were used for validation of the model's predictive transitions.

4. Conclusion

This study underscores the pivotal role of education in enhancing productivity within the textile sector, validated through a robust analytical framework integrating Cronbach's alpha, DT analysis, and MC simulations. The psychometric results confirmed that training constructs, particularly education, exhibit high internal consistency, reaffirming their reliability in assessing productivity-related outcomes. DT analysis established education as the most influential factor among the considered variables, enabling informed decision-making in resource prioritization for skill development. The two-step MC model provided a probabilistic understanding of productivity transitions, revealing the upward mobility potential of workers post-educational intervention, especially at primary and secondary education levels. The findings have practical implications for policymakers and industry leaders, enabling them to design evidence-based training programmes that enhance workforce capabilities, support lean practices, and sustain competitive advantage. This integrated approach demonstrates that data-driven educational planning is critical to advancing operational efficiency and economic performance in textile manufacturing.

Future research should examine the cost-effectiveness of such educational interventions, particularly in SMEs with limited resources. Additional applications of the α–DT–MC framework in other industries, such as healthcare and automotive manufacturing, could test its generalisability. Moreover, integrating real-time AI monitoring into the MC model could provide dynamic productivity forecasts, enhancing its utility for policy and industry decision-making.

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