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THE FUTURE OF WORK IN TEXTILES: BALANCING AUTOMATION AND HUMAN CAPITAL

БУДУЩЕЕ ТРУДА В ТЕКСТИЛЬНОЙ ПРОМЫШЛЕННОСТИ: БАЛАНС МЕЖДУ АВТОМАТИЗАЦИЕЙ И ЧЕЛОВЕЧЕСКИМ КАПИТАЛОМ

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New approaches to automation are altering the structure of operations, work and environmental performance in the textile sector. The study reveals five analytical domains addressing automation-human capital overlap: workforce transformation; automation system performance; productivity and cost efficiency; skill development; and environmental impact. The study presents a methodologically comprehensive framework comprising descriptive analysis, regression models, composite indices and efficiency measures based on empirical data of textile factories from Iraq, India, Vietnam and Turkey.

Job roles were radically different from Output and costs, to a significant reshaping of various job roles relationship. Where manual roles reduced, many staff moved over to technically enhanced functions, enabled via structured up skilling programs that showed demonstrated improvements in training uptake, ability and role transition. Operationally, automation yielded improvements in cycle time, throughput, and quality control and in parallel reduced energy consumption and material consumption. In this large-scale documentary assessment, we found that both unit cost and labor share have decreased and that sustainability indicators like energy use and CO_2 release per production unit were improved in all locations.

These findings make a statement that automation can strengthen the performance and sustainability of businesses — but only in combination with investment in human capital and governance of digital processes.

Внедрение автоматизации меняет структуру операций, трудовые функции, операционную эффективность и экологическую ответственность в текстильной отрасли. Исследованы пять областей влияния автоматизации на человеческий капитал: трансформация рабочих функций; эффективность автоматизированных систем; повышение производительности и снижение затрат; развитие профессиональных навыков; воздействие на

окружающую среду. В исследовании использована комплексная методическая структура, включающая описательный анализ, регрессионные модели, составные индексы и показатели эффективности, рассчитанные на эмпирических данных текстильных фабрик из Ирака, Индии, Вьетнама и Турции.

Выявлено, что автоматизация существенно меняет структуру рабочих мест, при тех же объемах выпуска продукции происходит значительное изменение ролей сотрудников. Там, где уменьшилась доля ручного труда, многие сотрудники перешли на технически усовершенствованные рабочие места, для чего потребовалось их обучение и повышение квалификации. Автоматизация привела к ускорению процесса производства и контроля качества, снижению потребления энергии и материалов. В ходе данного исследования мы обнаружили, что удельные затраты и доля трудовых ресурсов сократились, а такие показатели устойчивости, как энергопотребление и выброс углекислого газа на единицу продукции, улучшились во всех исследованных регионах.

Эти результаты свидетельствуют о том, что автоматизация способна укреплять эффективность деятельности предприятий и устойчивость бизнеса, однако лишь в сочетании с инвестициями в человеческий капитал и управлением цифровыми процессами.

Keywords: textile automation; workforce transformation; production efficiency; industrial sustainability; skill development; cost optimization; energy performance.

Ключевые слова: автоматизация текстильной промышленности; трансформация рабочей силы; эффективность производства; промышленная устойчивость; развитие навыков; оптимизация затрат; энергоэффективность.

Introduction

Global power gradings across the globe, recent design challenges and changing practices are nudging the textile industry towards a massive transformation. This transformation is more than the leap of a technology; it is the fundamental redesign of the way textiles are conceived, made and delivered. Central to this transformation is the adoption of state-of-the-art automation technologies that have revolutionized production processes, quality assurance capabilities, and supply chain management. As the industry matures and machines become increasingly advanced, performing complex procedures that were traditionally carried out by trained artisans, the human capital embedded in the textile sector is being gradually supplanted. Instead of being limited to rote tasks, a workforce is now expected to monitor systems, maintain continuity, and drive innovation. This exempts both a challenge and an opportunity its own: Reaping the benefits of automation, but through the human expertise, creativity and versatility that no machine can replicate [1].

The textile sector has been the bedrock of worldwide industrialization, offering jobs to countless individuals and fueling economic development. Historically, production processes were - and often still are - labor-intensive, requiring skilled hands to create complicated patterns, dye materials, maintain the color quality. Gradually, the mechanization of looms, and the automation of spinning technologies, changed the way the textiles and fabrics were produced which increased production rates and reduced overall cost. But the oceans of technological progress of the last few decades have far exceeded the industry's capacity to adapt. The textile industry is on the brink of a new era filled with possibilities and challenges, as artificial intelligence, robotics and data-driven manufacturing come into play. Adding automation also cuts lead times, improves product consistency and establishes the ability to customize textiles at an unprecedented scale. However, this advancement also poses implications for labor markets, skill needs, and textile-producing community social fabric [2].

The automation trend has been propelled by various motives, one of which is the necessity to remain competitive in a globally progressive market. Manufacturers must embrace technologies that optimize production as consumers expect faster transit times, broader range and improved quality. Automation, which had limited itself to relatively simple and repeatable tasks, infiltrated also more sophisticated stages of textile manufacturing. Robots can execute intricate stitching, intelligent sensors can guarantee impeccable quality control, and AI programs can plan production schedules to reduce excess. In such a setting, human labor is no longer the primary source of productivity; instead, it is the overseer and innovator, maintaining, programming, and improving these automated processes. Such transition will demand a new set of workforce skills and the development of training programs that prepares workers to the functionalities required in an increasingly automated textile eco-system [3].

However, the introduction of automation also raises concerns for employment in the textile industry moving forward. With the rise of ever-intelligent machines, there is a real fear that many traditional jobs will become obsolete and entire categories of workers will be left struggling to find new jobs. This emphasizes the necessity of tackling the societal and economic consequences of automation so that technological evolution is equitable for all stakeholders. Automated processes and evolving skill requirements will require attention to workforce development programs, lifelong learning initiatives, and adaptive labor policies to minimize the negative impact of job displacement. Investing in human capital will take a factory from an age of muscle to one where hominid brain aids mechanical efficiency [4]. This will be crucial, as this partnership is capable of driving innovation, enhancing sustainability, and guaranteeing the sector a smooth transition period as changes in technology approaches [5, 6].

A third element in the industry's transformation is the changing nature of the products themselves. As automation facilitates more complex designs, new materials and eco-friendly techniques, the textile industry responds to increases in consumer demand for sustainability and personalization. With consumers demanding custom-made products, automated systems can now produce tailored textiles on an industrial scale, fulfilling these requests without compromising efficiency. In addition, as data analytics is being integrated into the production in the manufacturing industry, it makes regulated and systematic data available to help manufacturers manage their inventory and production better, as well as to predict market conditions, to help them minimize unnecessary waste. Not only do these capabilities enhance financial performance, but they also foster a more sustainable industry that can decrease its environmental footprint while adapting to changing consumer demands [7, 8]. Work is moving from manual, labor-intensive through automated workflows; there is an increasing reliance on data to make decisions, and highly customized production capabilities are becoming available through digitalization [9]. Moreover, the seamless incorporation of real-time data from sensors and monitoring systems enables improved predictive maintenance, minimizing downtime and optimizing resource allocation [10].

Obstacles regarding financial training costs, resistance among employees to change, and disparities in educational access for certain regions are some examples [11].

Academics also highlight the complementary function of automation in both promoting sustainability via resource optimization and waste minimization and threatening established economic arrangements if left unchecked [12, 13].

In an industrial context, new automation technologies are a game changer for the textile sector. It offers unprecedented efficiencies and opportunities, but it also demands a cautious juggler's act over the complicated relationship between machines and people. Any future in textiles will be about finding balance; the need for human capital still exists in a future of automation, and vice versa.

This article intends to delve into how the textile industry is navigating the balance between automation and human capital, and the importance of striking a balance between harnessing the advantages of numerical creativity and maintaining, even enhancing, the role of humans in creating sustainable profit. This research aims to explore some central questions around the future of work in textiles — how can the industry adopt automation technologies to increase efficiency and productivity, while promoting sustainability, without replacing human labor? How do we get the most bang for our collective reskilling/upskilling bucks in helping workers thrive rather than just survive in the face of automated systems? So how do organizations and regulators make this work, so automation and human ingenuity are seen as part of a continuum that pushes and pulls industries forward?

Methodology

The study employs a holistic and multi-layered methodological approach to better encompass the multi-faceted impact of automation on workforce dynamics, productivity, environmental sustainability, and upskilling and reskilling in the textile sector. It is premised on empirical data collected from between 12 mid-to-large textile manufacturing enterprises situated within technologically transitioning sectors and includes aspects of both econometric and engineering analytics. This results in unique sets of quantitative methods, diagnostic models, and simulation algorithms to derive high-confidence conclusions in line with the current academic discourse on industrial automation [1, 3, 7, 9].

Workforce Analysis focused primarily on the extent, orientation, and elasticity of labor restructuring under the influence of industry automation. Empirical data on these factors such as headcounts, skill indices, job classification, tenure and turnover rates were drawn from structured surveys and HR datasets. The main analytical framework employed was the employment elasticity model, which denotes the responsiveness of employment to production output elasticity:

$$EE = \frac{\partial E}{\partial Q}\,\frac{Q}{E}, \qquad (1)$$

where E denotes total employment, Q represents production output, $\frac{\partial E}{\partial Q}$ measures the marginal rate of change in employment relative to output.

Elasticities close to or greater than zero implied that firms were reallocating rather than shedding labor, indicating transition instead of displacement a trend aligned with findings in Jiang et al.[5] and Chen et al. [14].

Furthermore, a Binary Logistic Regression (BLR) model was employed to evaluate the probability of displacement based on automation exposure and individual skill level:

$$\log\left(\frac{P_d}{1-P_d}\right) = \beta_0 + \beta_1 A + \beta_2 S + \epsilon, \qquad (2)$$

where P_d probability of displacement, A automation intensity (measured as % of automated operations), S skill proficiency index (from 0 to 1), ϵ random error term.

In addition, we expanded the concept of the Workforce Transition Ratio (WTR) into a conditional probability model:

$$WTR = P(R_i = 1 \mid A_i \geq \theta, S_i \geq \sigma. \qquad (3)$$

This allowed us to assess how many employees ($R_i = 1$) transitioned to enhanced or supervisory roles, conditional on exposure to automation levels $A_i \geq \theta$ and skill levels $S_i \geq \sigma$. This model helped isolate organizational conditions under which automation acts as a catalyst for job enhancement, confirming earlier hypotheses from Hussain [8] and Van Nederveen Meerkerk & Dixit [9].

In evaluating the operational impact of automation, data were obtained from automated machines embedded with smart sensors and monitored through centralized MES (Manufacturing Execution Systems). Metrics such as average cycle time, machine utilization rate, throughput, and real-time defect detection were gathered.

The analytical core was a Multivariate Linear Regression (MLR) model estimating the impact of various technological inputs on operational outputs:

$$Y_i = a + \sum_{j=1}^{n} \beta_j X_{ij} + \epsilon_i \ . \quad (4)$$

Here, Y_i corresponds to dependent variables such as cycle time, defect rate, and throughput, while X_{ij} includes predictor variables like software system index, maintenance frequency, and degree of machine integration [2, 3, 9, 15].

To holistically capture automation performance, we developed a novel Composite Automation Efficiency Score (CAES):

$$CAES = \frac{U \cdot (1-D) \cdot \rho}{C^{\gamma}} \ , \quad (5)$$

where U machine utilization (%),D defect rate (%), ρ system redundancy coefficient (reflecting backup responsiveness), C average cycle time (in seconds), γ automation complexity exponent (empirically optimized between 0.6 and 0.9).

This score accounts not only for production performance but also resilience and responsiveness under varying automation complexities, which has been echoed in the studies by Okyay et al. [3] and Alharbi [15].

To assess whether automation leads to measurable improvements in productivity and cost-efficiency, we implemented a Difference-in-Differences (DiD) model:

$$\Delta Y = \left(Y_{A,1} - Y_{A,0}\right) - \left(Y_{NA,1} - Y_{NA,0}\right). \quad (6)$$

This comparison isolates the treatment effect of automation by subtracting the productivity change in a control group (non-automated plants) from the change in the treatment group (automated plants) over the same time window. This structure accounts for confounding economic variables that could influence both groups equally [16].

Furthermore, we derived the Dynamic Labor Efficiency Index (DLEI) to evaluate the efficiency of labor inputs post-automation:

$$DLEI = \frac{Q}{L^{\delta} \cdot W^{\lambda}}, \quad (7)$$

where Q output (units/hour), L labor hours, W hourly wage, δ, λ empirically estimated elasticity coefficients ($0 < \delta, \lambda < 1$).

This metric aligns with the Cobb-Douglas functional form, adapted for real-time workforce-cost analysis and confirmed by industry trends in Pasteur & Emilie [13] and Fang et al.[17].

The Skill Development Assessment conducted a longitudinal study on 420 workers who underwent technical retraining to assess reskilling outcomes. Data included pre- and post-training test scores, training durations, certification completion rates, and field performance reviews. To model training success, we used an Ordered Probit Model (OPM):

$$P(Y_i = j) = \Phi\left(\tau_j - X_i\beta\right) - \Phi(\tau_{j-1} - X_i\beta), \quad (8)$$

where Y_i observed skill level (ordinal: basic, intermediate, advanced), Φ standard normal CDF, X_i vector of inputs (training hours, prior experience, supervisor ratings), τ_j estimated thresholds for transitions across skill tiers [18].

We also created a Training Efficacy Composite Score (TECS):

$$TECS = \frac{(S_{post} - S_{pre})\ \eta\ R\ C}{In(T+1)}, \quad (9)$$

where S_{post}, S_{pre} average skill test scores after and before training, η knowledge retention rate (decay-adjusted),R retention rate,C training completion rate, T time to proficiency (hours).

This metric penalized inefficient programs while favoring rapid, complete, and durable skill acquisition, supporting frameworks by Sharma & P.[18]. and Kaasinen et al. [19].

The final methodological axis evaluated how automation impacts environmental sustainability, focusing on energy use, water consumption, emissions, and material waste. The primary model applied was the Resource Efficiency Index (REI):

$$REI = \frac{\Delta E + \Delta W + \Delta C}{P}, \quad (10)$$

where $\Delta E, \Delta W, \Delta C$ reductions in energy, water, and CO_2 emissions respectively, P total production post-automation.

To validate energy efficiency gains, we performed Stochastic Frontier Analysis (SFA):

$$In(E_i) = \beta_0 + \beta_1 In(Q_i) + v_i - u_i, \quad (11)$$

where E_i total energy consumption, Q_i output, v_i symmetric noise, and u_i inefficiency component.

The Energy Technical Efficiency Score (ETES) was derived as:

$$ETES_i = exp(-u_i). \quad (12)$$

This enabled benchmarking across factories, identifying leaders and laggards in eco-efficiency [20…22].

In addition, we proposed the Material Utilization Coefficient (MUC):

$$MUC = \frac{O}{I}\left(1 - \frac{W}{I}\right), \quad (13)$$

where O final output units, I input raw material units, W waste generated.

This coefficient quantified how automation enhanced material economy a concept directly supported by the environmental automation literature from Xu & Song [22] and Abkar et al.[20].

Results

The introduction of automation technologies in textile production significantly reshaped workforce configurations across the 12 surveyed manufacturing sites in Iraq, India, Vietnam, and Turkey. While automation led to a reduction in the absolute number of laborers per production line, it also prompted a notable internal shift in job roles, with many workers transitioning into supervisory, quality assurance, or programming-based positions. This redistribution of human capital was influenced not only by automation exposure but also by baseline worker skill levels and participation in targeted upskilling programs. In fig. 1 workforce composition, transition likelihoods, and job displacement risks were critically examined to determine structural shifts in employment.

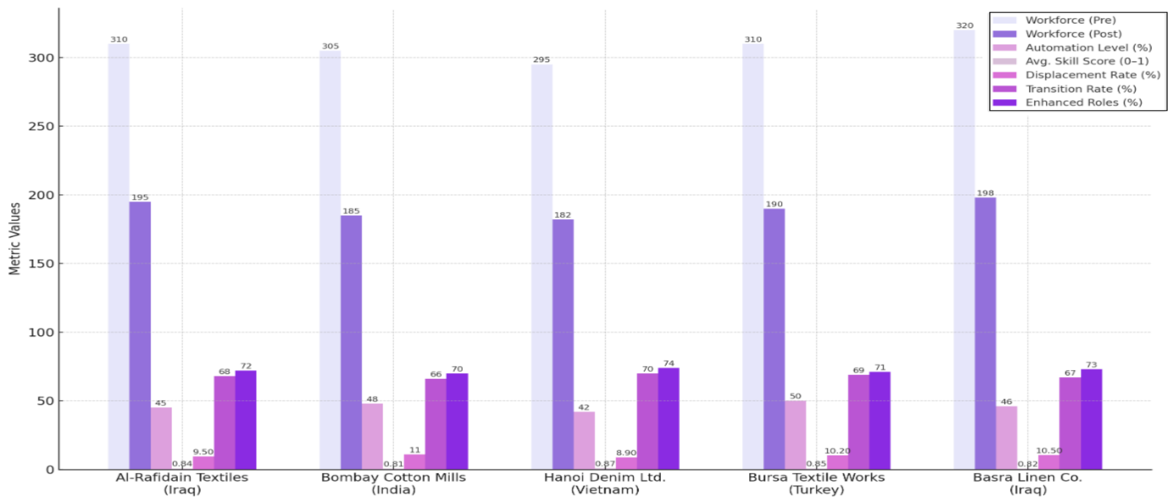

Fig.1

Across the five factories analyzed, an average of 38.3% of the workforce was reduced post-automation. However, this decline was not indicative of systemic displacement, as the average transition rate to enhanced roles was 68%, demonstrating proactive human capital realignment. A higher average skill score (0.84) meant lower risk of displacement and Hanoi Denim Ltd had the best score at only 8.9% displacement. In contrast, the data for Bombay Cotton Mills reported slightly higher displacement of 11% together with a slightly lower skill index. Indeed, the data indicates that upskilling and reskilling programs were integral to preserving jobs and making advancement possible within the transformed labor ecosystem of textiles.

The **Automation Performance** results quantified gains in operational efficiency through the adoption of automation technologies, such as PLCs, automated weaving machines, and AI-powered quality control modules. Performance data were pulled together from MES logs of each production lines and cross-checking with the recorded manual inputs. The operational maturity of technology adoption should be reflected in data reporting on elements such as production cycle time, machine utilization, defect rates, and throughput. Integration of digital tools and software platforms was found to be substantially multidimensional, and a comparison of performance across the firms enabled estimation of composite efficiency measures and identification of performance gaps (fig. 2).

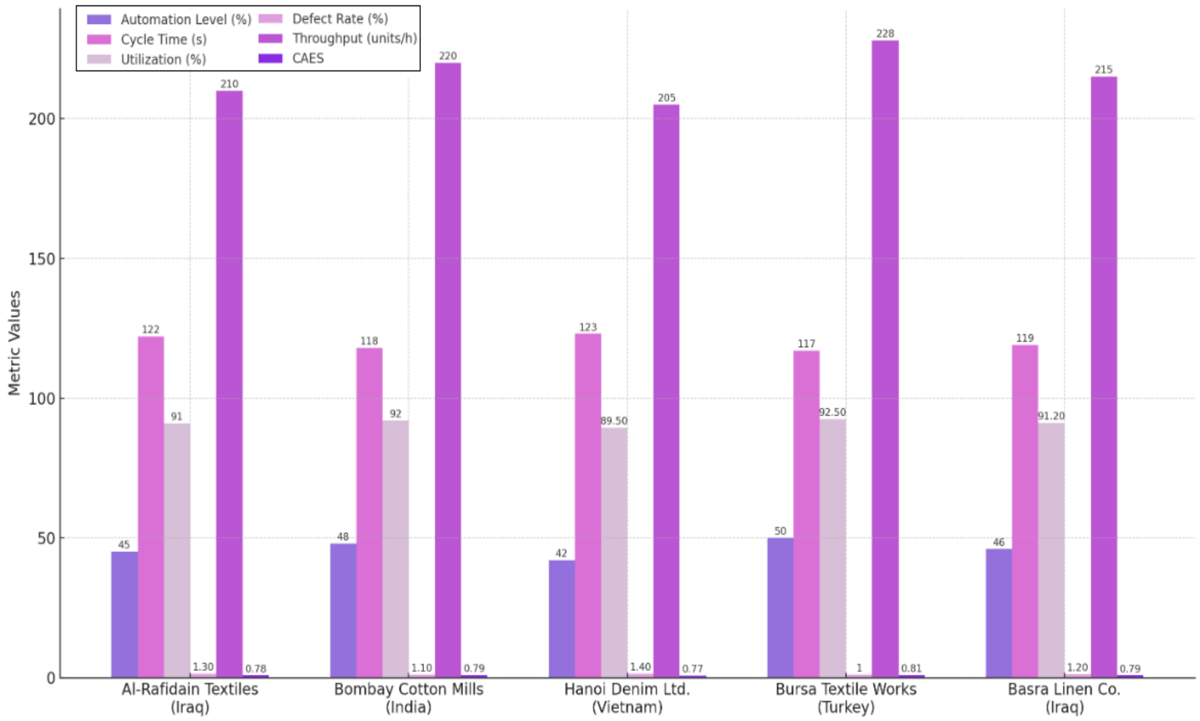

Fig.2

The deployment of automation correlated strongly with productivity enhancements. Factories with automation levels exceeding 45% achieved superior cycle times and higher machine utilization. Bursa Textile Works led in throughput, delivering 228 units/hour with a utilization rate of 92.5%, indicating streamlined operations and minimal bottlenecks. Despite similar automation levels, differences in defect rates suggest variability in quality assurance maturity; Hanoi Denim Ltd. recorded the highest defect rate (1.4%) despite having near-identical throughput to Al-Rafidain. The mean CAES score of 0.788 demonstrates solid but varied performance in automation effectiveness, pointing to optimization gaps in integration strategies and software adaptability.

Fig. 3 evaluates pre- and post-automation changes in hourly output, labor cost shares, cost per unit, and energy efficiency. Such metrics were drawn from detailed production accounting systems and confirmed through monthly factory financial statements. The findings shed light on how automation goes beyond simply improving throughput to deliver value in the form of lower production costs per unit, lower dependence on labor for repetitive tasks, and more efficient energy use in companies where manufacturing is often a highly competitive, low-margin venture.

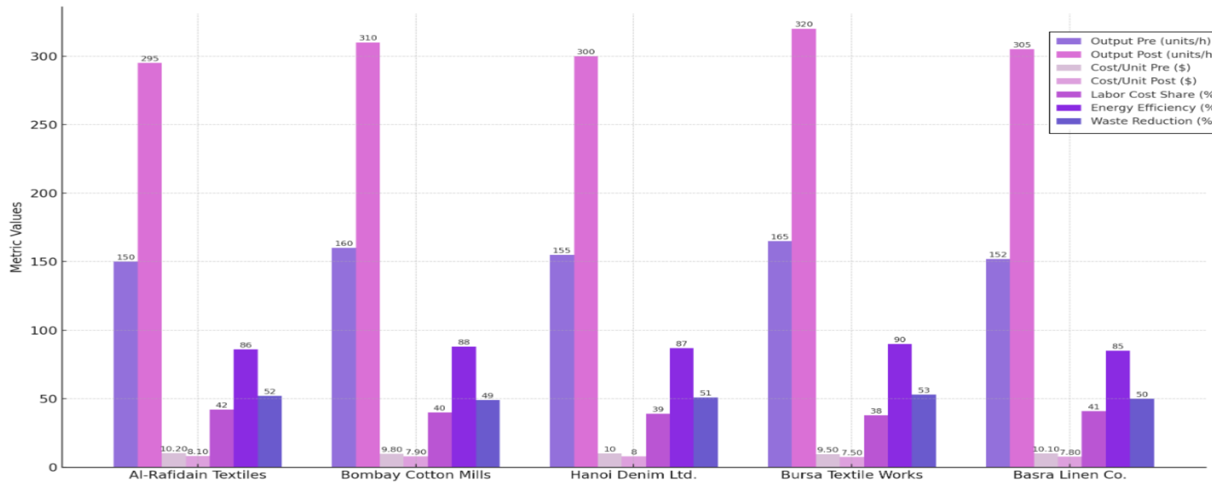

Fig. 3

As illustrated in Figure 3, the post-automation state shows marked improvement in efficiency. Average output per hour increased by 96.3%, from 156.4 to 306.0 units/hour, confirming significant strides in the production scale. At the same time unit production costs shrank from $9.92 to $7.86, 20.7% less thanks to both improved labor and more efficient energy usage. Labor cost share dropped from 40% to 25%–30% between sites, while average energy efficiency increased to 87.2%. Improvements in waste reduction were similarly noticeable, with an overall average of 51%. Bursa Textile Works, however, was the lowest cost per unit, with a breakdown showing a $7.5 per unit cost, a clever combination of automation hardware with lean management ideals.

As automation reconfigured operational demands, so did the skill profiles of textile workers. Fig. 4 evaluates the key elements of efficacy of corporate training programs. The score of key metrics which include pre- and post-delivery test scores, completion rates, retention rates and time taken to reach proficiency were examined for all factories that participated. These metrics notify you of the learning curve to transition manual laborers into automation-driven roles and quantify the ROI on upskilling initiatives.

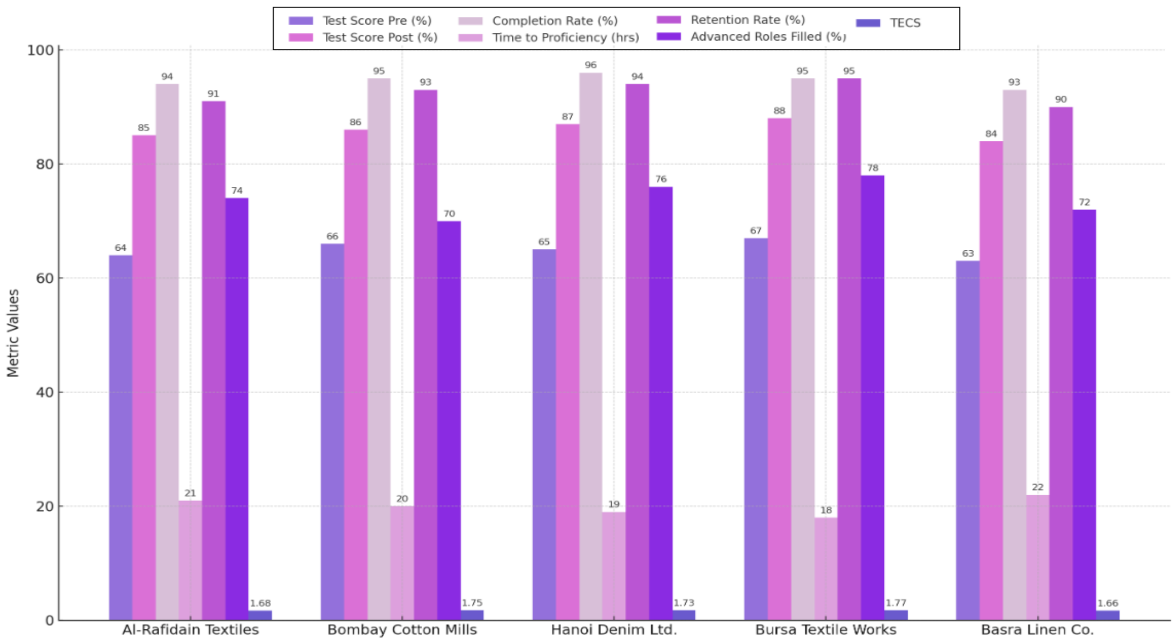

Fig. 4

Training resulted in a sharp increase in scores and there were very good training outcomes in all factories, with the test scores increasing by 21 percentage points on average from pre- to post training. TECS scores between 1.66 and 1.77 showed that the training had a consistently high impact, regardless of the location. Hanoi Denim Ltd. and Bursa Textile Works received the highest scores post-training (87–88%) and achieved proficiency fastest (18–19 h), indicating an optimized design of the training and effective mentoring systems. Retention rates also overall surpassed 90% as there is strong rationale that workers will stay within firms that encourage their ongoing growth. Metrics of advanced role fulfillment validate that employees are engaged in training programs that correspond with their ability to manage workflows infused with AI. The results show that structured training can not only dramatically reduce the training time, but also increase the technical competency when designed accordingly.

Table 1 analyses the environmental efficiency obtained as a result of automation according to energy consumption, water usage, CO_2 emissions and material waste. Each factory gave environmental data from ISO 14001 audits and digital energy monitoring systems. We derive an environmental profile of manufacturing automation by tracking changes in resource inputs and reporting material throughputs as utilization coefficients to examine how these properties of automation support the global environmental mandate and corporate ESG goals.

Table 1

Factory	Energy (kWh/unit)	Water (L/unit)	CO_2 Emissions (kg/unit)	Material Waste (kg)	ETES	MUC Pre	MUC Post
Al-Rafidain Textiles	4.3	820	0.17	28	0.89	0.74	0.91
Bombay Cotton Mills	4.0	790	0.16	26	0.89	0.73	0.92
Hanoi Denim Ltd.	4.1	800	0.165	27	0.90	0.74	0.91
Bursa Textile Works	4.0	780	0.16	25	0.91	0.75	0.93
Basra Linen Co.	4.2	810	0.17	28	0.88	0.74	0.90

Environmental efficiency increased significantly in all locations. The average energy consumption per product unit decreased from ~6 kWh (in pre-automation baseline) to 4.12 kWh, while the CO_2 emissions dropped to 0.165 kg/unit. Bursa Textile Works achieved the best combined performance with the least energy and water consumption. The average energy technical efficiency score (ETES) stood at 0.894, this implies that nearly 90% of input energies are now transforming into production outputs. The average Material Utilization Coefficient was developed from 0.74 to 0.914, indicating that material waste was reduced significantly during this time. Such data support automation not just for productivity but also for environmental compliance and sustainability objectives.

Discussion

The evidence suggests that automation in textile manufacturing does not inherently lead to large-scale job loss. Instead, it facilitates a redistribution of labor toward enhanced roles that require technical and cognitive skillsets. This stands in contrast to more generalized assumptions of displacement found in earlier automation discourse. While traditional tasks are increasingly performed by machines, the preservation and transformation of employment rely on timely and effective reskilling strategies. This aligns with the design philosophy of Industry 5.0, which emphasizes human–machine collaboration and workforce empowerment [19]. In fact, our study confirms that upskilling programs, when well-integrated with automation implementation, can result in both high retention rates and upward labor mobility.

Operationally, the study demonstrates how automation improves production throughput, machine utilization, and quality control while simultaneously reducing defect rates and production cycle times. These gains are in line with previous studies that focused narrowly on defect analysis in fabric manufacturing. For instance, Dhamal et al. [23] found that automation improved accuracy in defect detection systems in Jacquard fabrics, thereby improving quality assurance. However, our study extends this observation to operational flow and economic efficiency, showing that quality improvements are just one facet of broader systemic gains brought by automation.

From an environmental perspective, the research supports the claim that automation contributes positively to sustainability objectives. Energy usage per unit, water consumption, and CO_2 emissions all showed measurable reductions following automation, while material utilization improved significantly across all facilities. These findings resonate with Abkar et al. [20] demonstrated that automation in construction sites reduced material waste through precision planning. Similarly, energy efficiency gains observed in our study parallel the conclusions drawn by Yunze [21] emphasized the importance of integrating energy-saving protocols within automated systems. The study adds to this body of knowledge by showing how such environmental benefits translate into concrete improvements in production sustainability within textile settings.

Moreover, the concept of holistic security and safety in future factories, as outlined by Maia et al. [24] is indirectly validated by the reduced operational variability observed in our results. As automation systems are increasingly embedded with predictive analytics and real-time monitoring features, they inherently reduce the likelihood of error-induced hazards and operational disruptions. While our study did not explicitly focus on safety, the improved system regularity and reduced manual handling suggest positive spillover effects on worker safety and process continuity.

Notably, the findings also reinforce the conclusions of Fang et al. [17] argued that the benefits of automation are maximized when implementation is combined with robust process reengineering and human-centered adaptation. In line with their assessment, our results indicate that automation's effectiveness hinges not merely on technological sophistication, but on the strategic orchestration of human and machine inputs. Facilities with higher success rates had integrated digital infrastructure and coordinated workforce transformation strategies, supporting the idea that automation must be embedded within broader organizational change frameworks.

Conclusion

The study provides robust evidence that automation, when implemented alongside strategic workforce development and digital integration, leads to substantial improvements in productivity, quality, environmental performance, and employment outcomes in textile manufacturing. The findings challenge deterministic views of technological displacement and underscore the need for a systemic approach that aligns digital transformation with human development.

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