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Research paper

A Certain Investigation on Impacting Factors on A Textile Manufacturing Automation Using Industry 4.0 and Information Technologies

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Abstract

The role of Industry 4.0 in the textile industry improves its efficiency over operational and management layers. This includes automation of field sensors, scheduling of operating machines, automated assembly, and production lining. The automated device configuration and machine organization are facilitated using different smart controllers and machine learning algorithms. Therefore, the growth of textile industrial automation combines smart hardware and intelligent algorithms to maximize operational and production efficiency. This article presents a detailed survey of different learning algorithms and information technology incorporations in the textile industry. The impacting factors based on investment, production quality, and governance support are discussed through graphical representations and deep discussions. Therefore, this article considers the real-time data collected from the Coimbatore, Tirupur, and Erode regions of Tamil Nadu, South India. As these cities are considered hubs for textile processing and garment manufacturing, the data collected is prominent for analysis and discussion. Based on the discussion, the conclusion regarding the need for textile automation and the incorporation of Industry 4.0 is given.

Keywords: *Automation; Data Analysis; Industry 4.0; Information Technology; Textile Industry.*

1. Introduction

Various information technologies are employed in textile industries, which elevates overall production and performance. Information technologies provide sufficient techniques and services to design the necessary platforms for improvement [1]. Emerging industrial technologies (EIT) are also implemented in textile industries, which reduce the challenging issues during manufacturing. EIT uses autonomous robots to design the products as per the customer's preferences and tastes [2]. EIT maximizes the organization's sustainability, productivity, and impacts on the industries. It also minimizes the energy consumption level during production, which leverages the efficiency and significance range of the textile industries [3]. Industry 4.0-based decision-making model is used in textile industries. The decision-making model employs a comprehensive analysis technique that analyzes the features and patterns of production services [4]. The analyzed features are used to improve the industry by implementing enormous techniques. A content analysis technique is also used to evaluate the featuring factor that is required to enhance the development range of the industries [5].
Industry 4.0 is used in the textile industry, which facilitates the functional quality of the systems by providing automation services. Industry 4.0-enabled textile industries are used to enhance the sustainability rate of the systems [6]. Industry 4.0 is used to manage sustainable supply chain management (SSCM) in textile industries. Industry 4.0-based SSCM is one of the emerging technologies that provides significant path-planning services to textile factories [7]. SSCM requires a proper theoretical framework that identifies the categories and priorities to perform tasks in the industries. The SSCM is used to elevate the economic rate by minimizing the computational cost range of the systems [8]. Industry 4.0-based automation model is also used in the textile industries, which produce effective services. Autonomous robots are used here via Industry 4.0, which splits or divides the work and assigns it to the robots. Autonomous robots elevate the automation process, which prioritizes the sustainability and feasibility range of the industries. Industry 4.0 reduces the challenges and issues that cause latency in production and development processes. Technologies such as edge computing, machine learning (ML), artificial intelligence (AI), and automation are used in Industry 4.0 to process the data at the required time. An improved automation, data processing, analysis, resource allocation, scheduling, and optimization processes are designed to reduce the latency rate in production services. The data that are collected from various sources are processed to provide effective decision-making services within a required period. Industry 4.0 minimizes the delays and cost rate of the system by enhancing the connectivity and automation of streamlined processes. It also elevates the adaptability, reliability, and efficiency range of the systems. It influences the entire textile industry to perform tasks that enlarge the capability and robustness level of the industries [9], [10].

Various technologies are implemented and adopted in the textile industries which are in Asian countries. Corporate depreciation practice is used in the Japanese textile industry. The practice is used to normalize the choices that are identified as time and energy-consuming in the industries [11]. The long-term funds are used to facilitate the practice of fulfilling the demands. It is used to examine the demands and provide services based on priorities [12]. The depreciation practice influences the industries to perform necessary processes that improve the production and functional growth of the industries [13]. Digital empowerment is employed in the textile industry, which is used to increase economic stability. Digital technology is used to elevate the environmental aspects of China's textile industries [14]. In developed countries like China, digitalizing everything to improve sustainability and to market their products in this competitive world. Digital implementation in the textile industry provides relevant elements and functions to govern the necessary services to enhance production. Digital technology maximizes the overall sustainability and performance range of textile industries [15].

The Indian textile industry also adopts smart technologies to optimize the problems that impact over-production. Industry 4.0-enabled textile industry in India leads to significant problems. A multi-criteria decision-making (MCDM) method based on rough set theory is used to optimize the problems. The MCDM method mobilizes the issues as per severity [16, 17]. A severity assessment approach is employed in the method to assess the actual severity stage of the problems. The approach provides the exact severity score, which minimizes the computational cost rate during the optimization process [18]. The unwanted optimization issues are eliminated, which enlarges the feasibility level of the industries. The MCDM method is adopted to improve the production and performance range of the industries [19]. Smart technology causes certain barriers in the textile industry in India. Interpretive structural modeling (ISM) using smart technology is employed in industry, which leads to solving unnecessary challenges. ISM analyses the problems and provides the necessary solutions to solve the optimization problems of industries. It analyzes the critical issues with problems and eliminates the impact on the industries [20].

The article's contributions are:

1) The discussion of various methods presented by different authors for textile industry automation and the inclusion of Industry 4.0 concepts for efficiency-centric outcomes
2) The summary of the related works based on different parameters and constructive efficiency is tabulated.
3) The dataset-based analysis and discussion through different graphical analyses considering the impacting factors are presented
4) The summary of the study, concluding the remarks, and the need for automation in the textile industry, with the achievements so far

The organization of the article is as follows: Chapter 2 presents the related works, followed by the analytical discussion in Chapter 3 and Factor-based analysis in Chapter 4. Chapter 5 concludes the article with a summary of the above.

2. Related works

Ku et al. [21] designed an automated sewing system using machine vision for smart garment manufacturing. The actual patterns and features of the fabrics are captured via machine vision, eliminating the computational cost. A specialized algorithm is employed here to detect the narrow seam line that is required to design garments for the customers. The designed system elevates the performance range of smart garment manufacturing.

Kim et al. [22] introduced an E-textile-based wavy surface flexible antenna for battery-less sensor platforms. The introduced model is used to reconfigure the frequency via circuits. The model is used to detect and eliminate the parasite component that causes issues with the antenna. The model also reduces the frequency, which elevates the flexibility level of the systems. The introduced model improves the efficiency level of the platforms.

Yang et al. [23] designed cotton fiber-based cellulose fabrics for the textile and fashion industry. The designed approach is used for 3D printing in textile applications. The approach is used to adjust the cellulose for the printability of the link during 3D printing designs. A comparative investigation of the waste cellulose fabrics to improve moisture absorption is introduced. The designed approach improves the feasibility and effectiveness of the systems.

Xu et al. [24] developed a cleaner production (CP) evaluation system for textile industries. The method is used to evaluate the actual CP value in textile industries. The exact pollutant emission rate of the industries is calculated, which produces relevant data for the performance enhancement process. The method also analyses the indicator that contains differences between scores. The developed system maximizes the precision range of the evaluation process.

Perroux et al. [25] proposed a mixed-integer linear programming (MILP) model for flexible job shop scheduling problems (FJSSP) in the textile industry. The proposed model is employed to solve the FJSSP issues in the industries. It is used as a commercial solver that solves the most difficult problems that occur during manufacturing. Experimental results show that the proposed MILP model elevates the performance range of the industries.

Meeradevi and Sasikala [26] introduced an automatic fabric defect detection method using images for textile industries. The method uses a LabVIEW-based multiclass classification approach that classifies the exact types of fabrics. The method also analyzes the feasible datasets to detect the defects that cause issues in the design phases. The introduced method improves the accuracy of providing defect detection services.

Koundal et al. [27] designed a cell plug flow bioreactor (PFR) for textile industry effluent treatment. The designed model is used to treat the immobilized operations that cause more solid waste from the industries. It is used to elevate the total dissolved solids (TDS) ratio, which is extracted from the industries. It also lowers the color, biological oxygen channel, and demands. The designed model minimizes the computational cost and latency rate of the systems.

Oztat et al. [28] investigate the laccase enzyme activity of sludge in textile industry factories. The method is used to calculate the actual activity factors that are used for treatments in the industries. The method provides high oxidation and phenolic components to further the fabric design phases. The investigated method enhances energy efficiency and reduces the cost range of the factories.

Yang et al. [29] developed a modern intelligent manufacturing technology (MIMT) for the textile and garment industries. The developed technology is used to produce optimal resources and designs for the industries. The MIMT provides a proper foundation to construct or design patterns via fabrics. When compared with others, the developed MIMT improves the production level of the industries.

Kaur et al. [30] developed a smart manufacturing process for textile industry automation. The developed process uses a make-to-order (MTO) model to analyze the strategic development range of the industries. The MTO model allocates relevant resources to perform tasks for the manufacturing services. It is used to elevate the precision rate of interaction to promote smart manufacturing policies in the industries. The developed process improves the profitability, production, and performance levels of the industries.

Petrillo et al. [31] introduced an Internet of Things (IoT) enabled textile industry for sustainable transition. In this, IoT technology is used to elevate the sustainable development range of textile and producing regions in the industries. It also provides valuable insights to implement methods and techniques to design textiles for customers. The introduced model enlarges the maintenance and performance range of the textile industry.

Ribeiro [32] proposed an employment and green employment assessment method for textile industries in Portugal. A machine learning (ML) technique is employed here to analyze the discrete choices that eliminate the marginal cost rate. The method also analyses the impact of employment, which produces sufficient data for further processes. The method maximizes the overall accuracy rate of the assessment process.

Tahsin et al. [33] designed a fuzzy inference system (FIS) model for lean waste management. The model is used to eliminate the enormous amount of waste in Bangladesh's textile industries. It identifies the exact cause of waste and provides reliable solutions to reduce the waste ratio during production. The designed FIS model enhances the efficiency and productivity level of the industries.

Li et al. [34] investigate the industrial correlation spillover in China's textile industries. The actual industrial transfer and effects are analyzed to gather information for spillovers. The method uses an empirical analysis to analyze the industrial spillover during production. The method eliminates the computational cost and delay. The investigated method improves the performance range of the industries. In Table 1 (a), the key factors of the above-discussed methods are presented.

Table 1: A) Key Factors of the References

Reference	Field	Application	Computer Vision	Optimization	Machine Learning	Outputs
[21]	Garment Manufacturing	Sewing System	Yes	Yes	No	Sewing Automation
[22]	E-Textile	Antenna Model	No	Yes	No	Adaptable reconfiguration
[23]	Fashion industry	3D Printing	No	No	No	Printing study
[24]	Textile Industry	Cleaner Production	No	Yes	Yes	Comparative study
[25]	Textile Industry	Job Scheduling	No	Yes	No	Flexibility Improvement
[26]	Textile Industry	Defect Detection	Yes	No	Yes	High accuracy of detection
[27]	Textile Industry	Bioreactor Flow	No	No	Yes	Efficiency improvement
[28]	Textile Industry	Sludge treatment	No	No	Yes	Isolation accuracy
[29]	Textile/ Garment	Manufacturing Technology	No	Yes	Yes	Real-time application
[30]	Textile Industry	Automation	No	Yes	Yes	Uncertainty Mitigation
[31]	Textile	Sustainable technologies	No	No	Yes	Case Study
[32]	Textiles/ Apparels	Employment	No	Yes	No	Case Study
[33]	Textile Industry	Waste Management	No	Yes	No	Case Study
[34]	Textile Industry	Productivity Optimization	No	Yes	Yes	Industrial correlation

In the above tabulation, the key factors extracted from the considered references are summarized. In particular, the technology-based aspects of optimization, machine learning, and computer vision, the presence of parameters presence are analyzed. The target output across various purposes is also summarized in this tabulation. In Table 1(b), the pros and cons of the methods are presented with critical factor disclosure.

The critical factors disclosed in the above table indicate the problems faced in the automation process, exclusive in the textile industry. These critical factors are to be handled by the inclusion of advanced computations and AI paradigms with internal and remote-based controls. Artificial intelligence (AI) technology is employed in the textile industry to enhance the performance and production growth of the industry. AI-based methodologies are used here for maintenance, monitoring, modern integration, and automation services. AI technology uses high-level devices and techniques to increase the production rate without huge manpower. The competitiveness, quality, production, and efficiency of the textile industries are improved via AI technology. Blockchain (BC) technology is also used in the textile industry to improve the functional capability of the systems. BC tracks the condition of the supply chain, elevates the sustainability, real-time information sharing, and builds trust among customers. It also ensures the safety of the supply chain by analyzing the actual necessity of the resources to produce products for the customers. A BC-enabled model is used to stabilize the scalability and efficiency rate of the performance in textile industries.

Table 1: b) Pros and Cons of the Methods with Critical Factors

Reference	Pros	Cons			Critical Factor
		Flexibility	Energy Consumption	Mechanical Failures	
[21]	Low Computation Cost	Yes	No	No	Machine extensions are less
[22]	High flexibility	Yes	No	No	Scheduling
[23]	Self-Adjusting operations	Yes	Yes	No	Task allocation
[24]	High precision	No	Yes	No	Queuing
[25]	Fewer scheduling problems	Yes	No	Yes	Automation
[26]	Precision-based defect detection	No	No	Yes	Manual override at job stops
[27]	Low computational cost and latency	No	Yes	No	Task intervals are uneven
[28]	Energy efficiency	No	Yes	Yes	Automation
[29]	Productivity improvement	Yes	No	Yes	Expansion and integration
[30]	High precision and interaction rates	No	Yes	Yes	High device requirement
[31]	Fewer maintenance precision	No	Yes	Yes	Automation control and monitoring
[32]	Accuracy improvements	Yes	Yes	No	Task completion time
[33]	Overall efficiency	No	No	Yes	Machine-based expansions
[34]	Reduced Spillover	Yes	No	No	Job shop scheduling

3. Analytical discussions

The data used in this article is collected through 3 distinct modes: Google Forms (for personal contacts), direct company visits, and personal contacts in exhibitions. The data is collected from 50 companies out of 400 mid-sized companies in Coimbatore and Tirupur, located in

Tamil Nadu South India. From Coimbatore, Tirupur, and Erode, 22, 24, and 4 companies are selected, and their data sheets are used. These companies with the following elements are selected: a minimum of 3 pieces of equipment for manufacturing, 8 fabric producers, 10 garment manufacturers, integrated with 5 layers, and 24 yarn producers. The analytical representations below are presented and discussed based on the above collected data. The graphical assessments for adoption, efficiency, financial, and government policies are acquired from the collected data. This analysis follows the fundamental discussion of different impacting factors. The impacting factors are illustrated in Fig. 1.

The impacting factors tree is represented in Fig. 1; it is categorized under adaptation efficiency, financial, and governance. The sub-classification is defined based on organizations' interests and individuals' opinions on implementing Industry 4.0 in textile automation. As per the governance policies and support, there are wide opportunities to enhance the implementation of Industry 4.0 in textile automation. As Tamil Nadu is advancing in manufacturing, automation in every production is imperative. This is further augmented using Government schemes for infrastructure (for example: PM Mitra Mega Textile Park), production (PMKVY), and workforce improvement (skill development through MoUs). Based on the above data collected, the adoption of Industrial 4.0 for the textile organization is analyzed in Fig. 2. It presents the ratio of awareness of the potential benefits and its investment applicability. This analysis is presented under 5 opinions: strongly disagree, disagree, neutral, agree, and strongly agree. The benefits based on adopting Industry 4.0 for the existing textile processes and the opinion on investment to improve the performance and benefits are plotted in the above figure. The implementation of Industry 4.0 standards and technologies improves the operational and cost-cutting benefits of financial and precision outcomes. In this process, computational intelligence, smart hardware, machine learning, and infrastructure technologies are incorporated. These incorporations are used to increase the operational efficiency to achieve high productivity. The parameters based on opinion are analyzed in Fig. 3.

The efficiency is computed using performance (operational spinning, yarn, etc) and productivity (cloth outcomes) parameters. This efficiency encompasses input processing, power consumption, task completion, and cost allocation metrics. The organization that experienced the efficiency over manual processing and human interaction is compared before and after Industry 4.0 adaptation. The before and after adoption of Industry 4.0 achieves maximum difference, emphasizing the need for implementing/ upgrading automation in textile industries. However, the financial investments and prompt funding decide the improvements, trials, and testing of Industry 4.0 implementation. A free flow of economic allocations is useful in improving/ upgrading Industry 4.0 components. These upgrades are reliable in meeting the productivity demands and thereby improving the efficiency of the textile industry. However, the organization's opinion and individual's interest decide the industry 4.0 implementation/adaptation. The investment and secure funding assessments for the above are presented in Fig. 4.

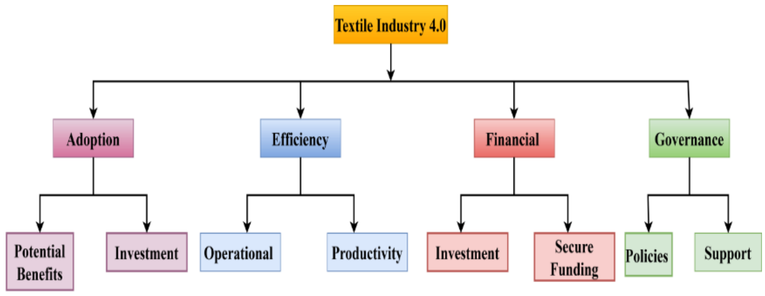

Fig. 1: Impacting Factor for Textile Industry 4.0.

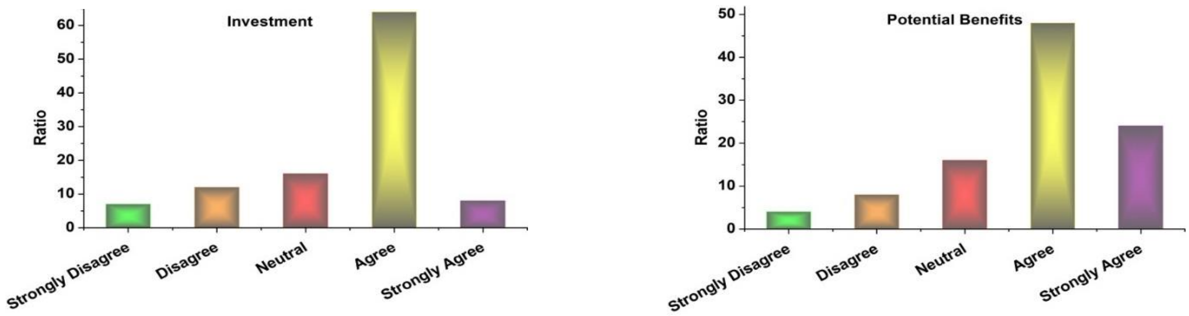

Fig. 2: Adoption Ratio Analysis for Investment and Potential Benefits Under Different User/ Consumer Satisfaction Levels.

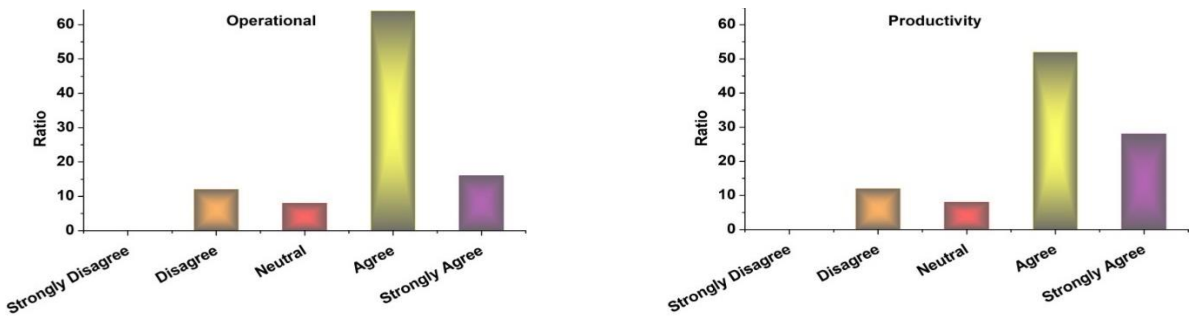

Fig. 3: Efficiency Ratio Analysis for Productivity and Operational Outcomes Under Different User/ Consumer Satisfaction Levels.

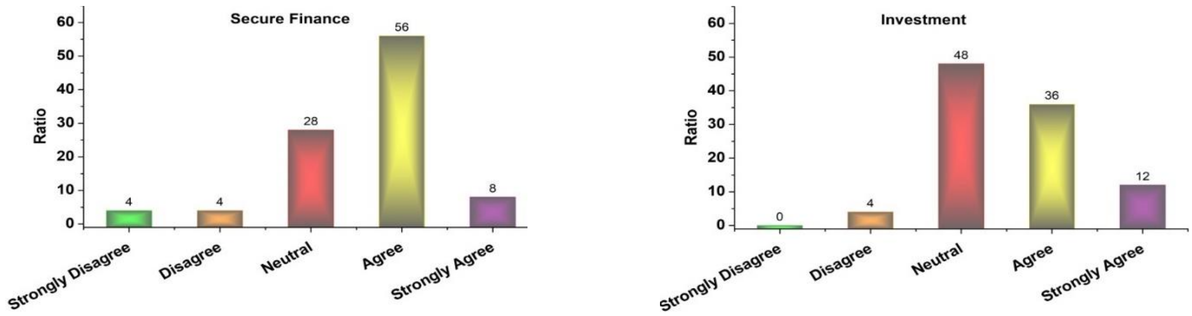

Fig. 4: Financial Ratio Analysis for Secure Finance Investment Under Different User/ Consumer Satisfaction Levels.

The opinions on investment and secure financing are useful in forwarding/leveraging the Industry 4.0 efficiency in textile manufacturing. The opinions are constructive for further implementations and investments. The investments are to be secured depending on the maximum availability and allocation. If these two parameters are reliable, the government policies and support for implementing the automation is likely to be high. The Indian Government provides various schemes and policies to enhance the production growth and development of the textile industry 4.0. The Prime Minister Mega Integrated Textile Region and Apparel (PM MITRA) scheme is one of the schemes for textile industry 4.0. The PM MITRA scheme is designed to develop large-scale and modern textile manufacturing facilities for the textile industry. The actual goal is to enhance the competitiveness and attract foreign investors to the Indian textile industry. The scheme also creates massive job opportunities and creativity in industries.

The Scheme for Capacity Building in the textile sector (SCBTS) or Smart Textile Scheme was also initiated by the Indian government for the textile industries. It is designed to provide skill-oriented, demand-driven, and development training services to the industries. The textile value chain among the workers is improved by providing feasible training sessions, which enhance the productivity level of the textile industries. The Smarth scheme also supports traditional handicrafts and handloom production in international countries. In Fig. 5, the opinions towards governance policies and support are analyzed.

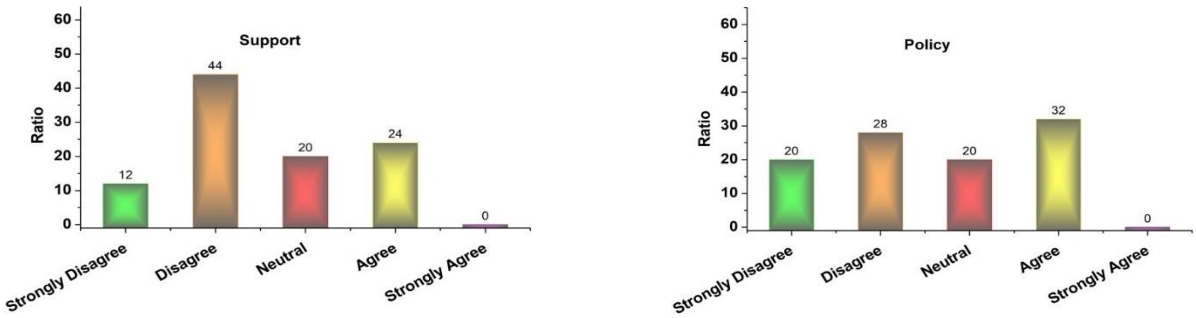

Fig. 5: Support Analysis and Government Policies Under Different User/ Consumer Satisfaction Levels

The opinion-based results for government policies and (infrastructure) support for aiding the development and establishment of Textile Industry 4.0 are presented in Fig. 5. The above analysis presents the acceptable opinion over governance policies and support provided for improving textile industry automation. Based on the maximum agreement towards policy adaptability and infrastructure support, further improvements in textile automation are made. In Table 2, the impacting factors considered in the references from [21] to [34] are summarized.

The consideration and existence of different impacting factors in the references are tabulated above. Based on the existence, the solutions with technological aspects are presented. The factor-based correlation is aided by different multi-objective parameters that serve the purpose of textile automation.

Table 2: Impacting Factors Considerations

References	Adoption Benefits	Investment	Efficiency Operational	Productivity	Financial Investment	Secure Funding	Governance Policies	Support
[21]	Yes	No	Yes	Yes	No	No	No	Yes
[22]	No	No	Yes	Yes	Yes	Yes	Yes	Yes
[23]	Yes	No	Yes	No	No	Yes	No	Yes
[24]	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes
[25]	No	No	Yes	No	Yes	Yes	Yes	No
[26]	No	Yes	Yes	Yes	Yes	No	Yes	Yes
[27]	No	No	Yes	No	Yes	Yes	Yes	Yes
[28]	No	Yes	No	Yes	Yes	Yes	Yes	Yes
[29]	Yes	Yes	Yes	Yes	No	No	Yes	Yes
[30]	No	No	Yes	Yes	Yes	Yes	No	No
[31]	No	No	Yes	No	Yes	Yes	Yes	Yes
[32]	Yes	No	No	Yes	No	Yes	Yes	Yes
[33]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
[34]	No	Yes	No	No	Yes	No	No	Yes

4. Factor-based correlation

Depending on the above analysis, further validations supporting textile industry automation are discussed. In Fig. 6, the awareness score and efficiency score for the investment score are illustrated.

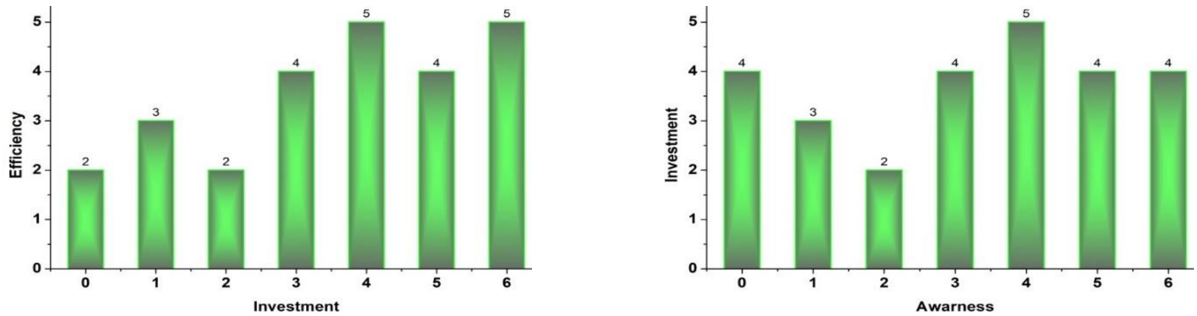

Fig. 6: Investment Awareness and Efficiency Score Analysis.

The investment factors are optimal in deciding automation awareness and efficiency through the knowledge of performance improvement. In this process, awareness is the first step for acquiring investment based on different efficiency outcomes. Therefore, the interconnected factors are responsible for leveraging the quality score under different successful textile automation processes. Following the above, the product quality scores for different investment scores are analyzed using Fig. 7.

The product quality score relies on the automation outputs identified post-task completion. In this process, the product quality is estimated based on delivery time, maximum satisfaction rate, and sustainability. Therefore, these features are administered through different ranges of investments. The investment score-based analysis for the government.

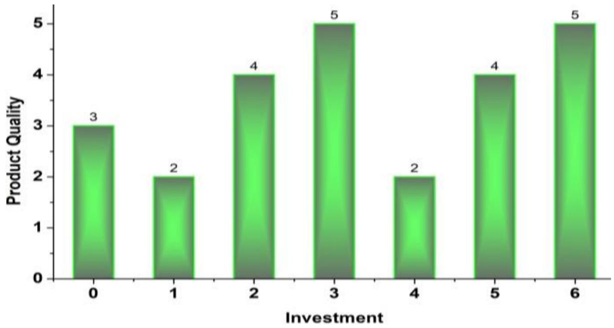

Fig. 7: Product Quality Score Analysis for Investment Counts.

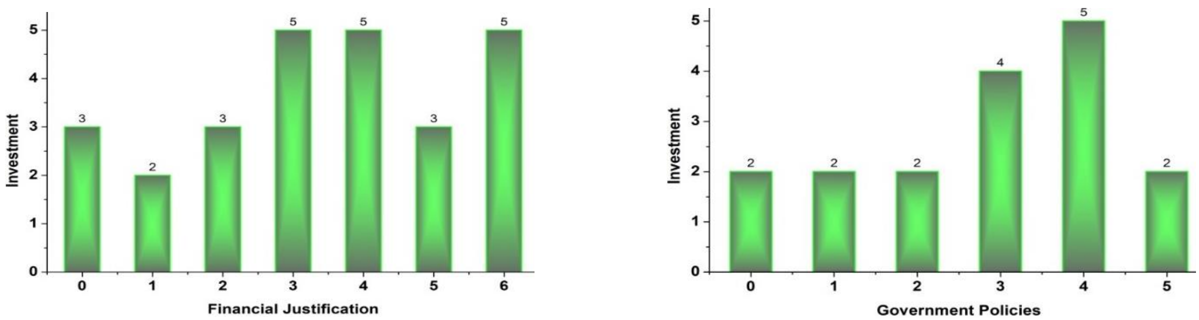

Fig. 8: Financial Justification and Government Policies Variants for Investment Numbers.

In the above analysis, the financial justification and the government's policies based on maximum investment are analyzed. The investment analysis follows different opinions depending on the support provided by the government for increasing productivity. Besides, the policies framed by the government are crucial in deciding the textile industry's economic status and profitable outcomes. Therefore, the adjustments and further investments in textile Industry 4.0 are reliable through government support and definitive, easily adaptable policies framed. The constructive support encourages further investment in textile automation, adopting new technologies and production outcomes. The summary of the different scores formulated with the matrix representation is presented in Fig. 9.

	Awareness Score	Investment Score	Efficiency Score	Product Quality Score	Fianancial Justification Score	Finding Challenges Score	Government Policies Score	Government Infrastructure Score
Awareness Score	1	0.47	0.48	0.38	0.20	0.18	0.08	0.03
Investment Score	0.47	1	0.531	0.540	0.371	0.350	0.190	0.230
Efficiency Score	0.48	0.53	1	0.330	0.36	0.18	0.11	0.21
Product Quality Score	0.38	0.54	0.83	1	0.26	0.29	0.18	0.34
Fianancial Justification Score	0.20	0.37	0.33	0.26	1	0.35	0.058	0.060
Finding Challenges Score	0.180	0.35	0.36	0.29	0.35	1	0.02	0.03
Government Policies Score	0.08	0.19	0.18	0.050	0.020	0.18	1	0.87
Government Infrastructure Score	0.30	0.230	0.210	0.340	0.06	0.030	0.870	1

Fig. 9: Confusion Matrix of Different Industrial Factors Scores.

The confusion matrix for different scores is represented in the above Fig. 9. The influence factor impact over different scores is summarized to ensure maximum integral feasibility of Industry 4.0 in textile manufacturing. The above representation is a cumulative opinion-based factor for deciding the scores across various impacting factors. This representation is improved through different assessments of impacting factors over the development and efficiency outputs observed. This is instigated using different trial-and-error implementations and congruent differentiation of information technologies, learning algorithms, and optimization methods. Therefore, the overall impacting factors for different outcomes and automation efficiency are reliable through the impact scores.

5. Conclusion

This article presents a survey and discussion of the impacting factors on textile industry 4.0 automation processes. The role of technical aspects and automation demands is identified using organizations' opinions and individuals' experiences. The data collected through different audits in person and Google Forms are used to evaluate the correlation between automation and textile industry performance. The impacting factors are differentiated using investment factors, based on which the outcomes are analyzed. The role of information technology and other automation methods are correlated over investment, product quality, and sustainable finance is discussed. Based on the illustrations and discussions, the significance of Industry 4.0 is analyzed under different efficiency-targeted automation in textile automation. The data collected from the textile hub cities of Tamil Nadu, South India, is utilized in this article to provide detailed discussions strengthening the role of Industry 4.0 and textile manufacturing.

This article presents a survey limited to the data collected from a specific region of Tamil Nadu, South India. However, the influencing factors are not the same throughout the world. Based on location, governance, transportation, import, export, taxation, etc., the impact of financial and technical factors on Industry 4.0 implementation varies. Therefore, without restricting to a certain or limited data, the analysis is planned to be extended for a wide range of data collected from across the globe. This would improve the technical and further real-time implementation problems of Industry 4.0 with independent influencing factors with flexible solutions.

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