Cureus Journal of Engineering

Open Access Original Article

Analysis of the Production Performance of Manufacturing Textile Products, Bahir Dar Textile Share Company, Ethiopia

Received 05/29/2025
Review began 06/05/2025
Review ended 09/16/2025
Published 10/31/2025

DOI:
https://doi.org/10.7759/s44388-024-00371-3

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Abstract

Background: The textile industry is the world's second-largest employer, a critical component of a country's economy, and provides numerous job opportunities. The study's goal was to analyze the production performance of the Bahir Dar textile share firm by examining how operational factors influence productivity in spinning, weaving, finishing, and garment manufacturing.

Method: This analysis used secondary data on the performance of textile manufacturing from January 2016 to December 2023. VAR models were used. While putative causal relationships were investigated using Granger's causality tests. Furthermore, the short-run interactions between the variables were discovered using impulse response analysis.

Results: The unit root tests of the studied series show that all of them were stationary after the first difference. The correction factors for garments, finishing, weaving, and spinning were -0.43, -0.33, -0.84, and -0.22, respectively. The lack of power, mechanical, and water supply had a severe impact on the spinning production process. The Granger causality test revealed that in the long run, spinning forecasted weaving, weaving forecasted finishing, and finishing predicted garmenting.

Conclusion: Mechanical faults, a shortage of electricity, a lack of water supply, and an insufficient supply of air to textile industry machinery all have a negative impact on product performance. The company should place a high priority on factors that increase productivity.

Categories: Data Science and Analytics for Engineering, Sustainable Textile Manufacturing, Textile Engineering and Innovation
Keywords: causality, forecast, impulse, stationary, var

Introduction

Textile is one of the areas that have received a lot of attention from the government, to become one of the world's top sourcing destinations [1]. The textile process is separated into numerous processes, including cotton treatment processing, yarn manufacture, and weaving, with advanced equipment frequently utilized for performance [2,3]. The textile industry primarily focuses on the design, manufacture, and distribution of yarn, cloth, and clothes [4]. The increasing population, as well as the growing use of such items in technical and industrial applications, has led to a significant rise in textile demand [5].

The textile industry is a substantial contributor to many national economies, encompassing both small and large-scale enterprises worldwide [6]. China has a massive textile sector globally, both in terms of production and exports. India is the world's third-largest apparel producer, after China and the United States [7]. Developing countries witnessed tremendous industrial expansion surprisingly early, in many cases before World War I, despite starting with relatively low levels of modern manufacturing output. Africa's tremendous economic boom began only during the interwar period, particularly after 1950. The "golden period" between 1950 and 1973 was the high point of industrial growth not only in these regions but also throughout the entire periphery [8]. Ethiopia's lengthy history in textiles began in 1939 when the first garment factory was built. According to Ethiopian data, the textile and apparel industry has developed at an average rate of 51% over the last 5 to 6 years, and more than 65 international textile investment projects have been licensed for foreign investors during this period [9].

Maximizing production performance in the textile industry is crucial for every factory's success and competitiveness. Productivity gains in the manufacturing sector are extremely important for all emerging countries, especially because they contribute to strengthening competitiveness and encouraging economic growth over time [10]. Global competition and technological advancements are forcing textile product manufacturers to reconsider their strategies, operations, processes, and procedures to survive. To remain competitive in today's global environment, manufacturing businesses must understand and measure the various elements of their performance [11]. The level of performance achievement is significantly "system" dependent [12]. The manufacturing function's quality assurance procedure and ability to offer a quality product or service were found to have a substantial correlation with company performance [13]. Production and services have a favorable impact on the performance of textile enterprises [14].

Total productive maintenance (TPM) methods have a favorable and considerable impact on manufacturing performance, considerably increasing cost effectiveness, product quality, on-time delivery, and volume flexibility [15]. Production inefficiency patterns that were difficult to spot using traditional quantitative reporting-temporal patterns of best and worst performing machines-were identified, as well as the most important drivers of inefficiency and their relationships [16]. The textile sector is creating expert systems applications to boost output, enhance quality, and minimize costs [17]. The performance of supply chain management and its importance in improving business activities in Ethiopia's textile industry is also a significant focus [18]. Low performance and competitiveness in the clothing industry are caused by inadequate performance assessment practices, limited financial capacity and productivity, excessive production costs, poor garment quality, poor logistics management, and bad customer and supplier relationships [19]. According to artificial neural network findings, the relationship between manufacturing production and energy consumption is relatively different at the disaggregated level [20]. Several finishing operations, including drying, curing, and heat-setting, need a significant amount of energy [21].

The textile sector is critical to a country's economy since it generates jobs, industrial growth, export revenue, and associated sector development while encouraging innovation, skills, and long-term economic progress. Previous research on Nigeria's manufacturing sector has identified key factors influencing its performance. One study found that labor force, gross fixed capital formation, and exchange rate have a positive long-term impact on manufacturing value added, while capacity utilization, lending rates, and government spending show weaker effects [22]. Another study confirmed a significant long-run (LR) relationship between manufacturing output and Gross Domestic Product (GDP), though its impact on employment was not statistically significant [23]. Inflation, interest rates, and currency rates all have a positive and considerable impact on the return on assets of Pakistan's textile weaving industry; however, foreign direct investment and trade openness have no effect on the return on assets of Pakistan's textile weaving sector [24]. National savings and labor force have a LR positive effect on manufacturing sector output, whereas exchange rates and inflation have a long-term negative effect. National savings, industrial labor force, inflation, and currency rates are all significant factors influencing the growth and survival of the manufacturing sector [25]. Gross fixed capital creation and health expenditure have a positive influence on industrial output in the short run in Nigeria, whereas unemployment, inflation, and exports have a negative effect [26]. Thus, studies have attempted to examine the performance of the textile manufacturing sectors by focusing only on the weaving and finished product, ignoring other factors that influence performance, and examining the quantity of money or exports made by the company on a monthly or annual basis to assess its performance. However, there is limited research literature on the production performance of each series (i.e., the amount of production created by the spinning, weaving, finishing, and garment processes) in these industries. This study addresses a gap in the current literature by providing a detailed, process-specific analysis of production performance using advanced time series modeling, whereas previous studies were primarily concerned with wider economic or aggregate performance indicators. It stresses the dynamic relationships between subsectors, providing insights into operational issues and paths for strategic changes in the textile industry.

In this study, Vector Autoregressive (VAR) models were utilized to determine the production performance of each textile product manufacturing process by involving production-impacting aspects such as air, number of mechanics, amount of electricity, number of employees, and water supply. The goal of using a multivariate time series model in a VAR framework was to evaluate the manufacturing performance of each manufacturing process, investigate the effect of one process on the other processes, and forecast one process based on the others.

Materials And Methods

Study design and setting

Between January 2016 and December 2023, a panel investigation was conducted. The data for this study come from Bahir Dar Textile Share Company. The Bahir Dar Textile Share Company was founded in 1961. The data were secondary information on the production performance of textile products. There were a monthly report that showed how the company produces its products in each process and on each independent variable. The VAR model was used to assess interrelationships between processes, anticipate future performance, and examine the impact of one process on the others. Granger causality tests and impulse response analysis were also used in conjunction with the VAR technique to study causal linkages and short- and long-term interactions between variables.

Operational definitions

Spinning is the process of pulling out and twisting fibers until they form a continuous thread or yarn. Spinning is a necessary prerequisite for weaving cloth from fibers that do not have excessive length [27].

Weaving is the process of interlacing groups of strands together to generate a woven fabric structure.

Finishing refers to the process that converts the woven or knitted cloth into usable materials, and more particularly, any technique conducted after dyeing the yarns or fabric to improve the appearance, performance, or hand feel of the completed textile or garment [28].

Garment production is an organized activity that includes sequential procedures, including laying, marking, cutting, sewing, inspecting, finishing, pressing, and packing [29].

Measurement of variables

The dependent variables included were spinning (in tons), weaving (in kilometers), finishing (in square kilometers), and garments. The independent variables included were air (million liters), mechanics (number), employees (number), water (cubic meters), and electricity (kilowatt hours).

Statistical analysis

The Augmented Dickey-Fuller (ADF) test for stationarity. The Phillips-Perron (PP) unit root tests differ from the ADF tests primarily in how they handle serial correlation and heteroscedasticity in the errors [30]. The multivariate time series is modeled using the VAR model [31]. The VAR models enable the analysis of dynamic interrelationships between many variables across diverse processes. Co-integration occurs when two or more series are independently integrated, yet some linear combination of them has a lower order of integration [32]. The fitted model was validated using the Portmanteau autocorrelation test, the autocorrelation Lagrange Multiplier (LM) test, the Autoregressive Conditional Heteroskedasticity (ARCH) test for heteroscedasticity, the Jarque-Bera test for normality, and information criteria such as the Akaike Information Criterion (AIC), Schwarz Criterion (SC), and Hannan-Quinn Criterion (HQ) to select the optimal lag lengths and model specifications. Granger causality tests were the first tool used to investigate the link between variables of interest. Granger causality is concerned with linear prediction, and it only has "teeth" if one event occurs before another, or if Granger causality is only found in one direction. It evaluates whether one item occurs before another and helps anticipate it, but nothing else [33]. Granger causality is important in this study since it identifies directional predictive links among the sub-sectors. This knowledge contributes to a better understanding of the movement of influence within the textile manufacturing chain. The Impulse Response Function (IRF) gives the jth period response when the system is shocked by a one-standard-deviation shock [34]. Impulse response analysis, on the other hand, determines how shocks or variations in one variable affect other variables across time. It quantifies the short- and long-term effects of such shocks, revealing how an innovation in one process influences subsequent processes across time.

Results

Nature of the data

According to Table *1*, the correlation matrix between dependent variables revealed that almost all variables were strongly connected. However, the number of employees had a low correlation with all other variables.

Variables	Spinning	Weaving	Finishing	Garment	Air	Employ	Electrical	Mechanical	water
Spinning	1.00	0.75	0.93	0.93	0.89	0.09	0.89	0.72	0.87
Weaving	0.75	1.00	0.79	0.69	0.58	0.06	0.63	0.51	0.57
Finishing	0.93	0.79	1.00	0.96	0.91	0.03	0.95	0.69	0.91
Garment	0.93	0.69	0.96	1.00	0.96	0.05	0.96	0.73	0.94
Air	0.89	0.58	0.91	0.96	1.00	0.11	0.96	0.71	0.93
Employ	0.09	0.06	0.03	0.05	0.11	1.00	0.03	-0.23	0.03
Electrical	0.89	0.63	0.95	0.96	0.96	0.03	1.00	0.72	0.96
Mechanical	0.72	0.51	0.69	0.73	0.71	-0.23	0.72	1.00	0.69
Water	0.87	0.57	0.91	0.94	0.93	0.03	0.96	0.69	1.00

TABLE 1: Correlation matrix

As a result, in Table 2, the p-values for each series were more than the 5% level of significance for the ADF and PP tests, indicating that all series were non-stationary at level but stationary at first difference. This implies that all of the series were integrated with order one.

Variables	Test statistics		p-value		Decision
	ADF	PP	ADF	PP	
Spinning	0.41	-0.71	0.98	0.84	Not stationary
Weaving	-0.03	-0.85	0.95	0.80	Not stationary
Finishing	0.41	-0.85	0.98	0.80	Not stationary
Garment	0.06	-0.24	0.96	0.93	Not stationary
After first differencing					
Spinning	-14.82	-16.32	0.00	0.00	Stationary
Weaving	-11.45	-12.67	0.00	0.00	Stationary
Finishing	-12.54	-12.70	0.00	0.00	Stationary
Garment	-10.86	-15.54	0.00	0.00	Stationary

TABLE 2: Unit root test

ADF, Augmented Dickey-Fuller; PP, Phillips-Perron

The VAR model's appropriate lag duration was one (1), as the minimum AIC, SC, and HQ values occurred at lag one. As a result, in Table 3, it is assumed that VAR (1) is the best fit for the data.

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-2827.25	NA	1.06exp+17	50.56	50.66	50.60
1	-2464.81	692.51	2.19eexp+14*	44.37	44.86*	44.57*
2	-2448.79	29.46	2.19exp+14	44.37	45.25	44.73
3	-2435.87	22.85	2.32exp+14	44.43	45.69	44.94
4	-2416.66	32.58*	2.21exp+14	44.37*	46.02	45.04
5	-2409.43	11.76	2.60exp+14	44.53	46.56	45.35
6	-2401.87	11.75	3.06exp+14	44.68	47.10	45.66
7	-2385.21	24.68	3.08exp+14	44.66	47.48	45.81
8	2371.35	19.55	3.28exp+14	44.70	47.91	46.00

TABLE 3: VAR lag order selection

* indicates lag order selected by the criterion. VAR, Vector Autoregressive; AIC, Akaike Information Criterion; SC, Schwarz Criterion; HQ, Hannan-Quinn Criterion; LR, long run; FPE, Final Prediction Error

The estimated VAR model had a significant influence on the t-statistics value for spinning lag; the preceding spinning realization was associated with a 74% increase in real spinning on average, provided everything else remained unchanged. For weaving lag, earlier weaving realization was associated with a 72% increase in real weaving on average, provided all else remained constant. For finishing lag, the previous finishing realization was associated with a 101% increase in real finishing on average, provided everything else remained unchanged. For garment production lag, the preceding garment production realization was associated with a 78% increase in real garment output on average, providing all other factors remained unchanged.

Cointegration analysis

Table 4 demonstrated that the trace statistic for the series (48.66 > 47.86), the maximum eigenvalue test (33.39 > 27.58), and the p-value (0.0042 and 0.0074, respectively, less than 0.05) indicated that the system had at least one co-integration vector. This implies that the variables had LR relationship.

Hypothesized	Unrestricted Cointegration Rank Test (Trace)				Unrestricted Cointegration Rank Test (Maximum Eigenvalue)		
Number of case(s)	Eigenvalue	Trace statistic	Critical value (5%)	P-values	Max-Eigen statistic	Critical value (5%)	P-values
None *	0.1841	48.66	47.86	0.0419	33.39	27.58	0.0074
At most 1	0.1542	25.27	29.80	0.1521	19.25	21.13	0.0897
At most 2	0.0503	6.01	15.50	0.6939	5.93	14.26	0.6219
At most 3	0.0007	0.08	3.84	0.7759	0.08	3.84	0.7759

TABLE 4: Johansen Cointegration Test Results

After identifying that the variables in the VAR model appeared to be cointegrated, the next step is to estimate the short-run behavior and make changes to the LR models, which were represented by Vector Error Correction Model (VECM). Table 5 shows that the adjustment factors for garments, finishing, weaving, and spinning were -0.43, -0.33, -0.84, and -0.22, respectively. This refers to the proportion of the long-term gap closed in each month.

Error correction	D(Garment)	D(Finishing)	D(Weaving)	D(Spinning)
Co-integrating	-0.43	-0.33	-0.84	-0.22
D(Garment(-1))	0.36	0.88	-0.23	0.01
D(Finishing(-1))	0.33	-0.03	0.05	0.01
D(Weaving(-1))	0.11	0.41	-0.002	0.06
D(Spinning(-1))	0.14	0.89	0.66	0.43
Constant	-103.73	-662.79	-124.68	-169.25
Air	0.42	2.54	0.75	0.37
Employ	-0.049	-0.28	0.03	0.03
Mechanical	0.02	0.11	0.05	0.11
Electrical	4.7exp-06	1.6exp-05	1.1exp-05	3.9exp-07
Water	5.2exp-04	0.009	0.0002	-0.0002

TABLE 5: Estimated coefficients of the vector error correlation model

The number of mechanics had a significant impact on the spinning and garment manufacturing processes. The result is that advanced spinning machines increase fiber throughput, reduce waste, boost overall productivity, and ensure consistent yarn thickness.

The volume of air supply had a big impact on the garment production process. This indicates that maintaining consistent air pressure is critical for the operation of particular machines, influencing speed and precision.

The spinning, weaving, finishing, and garment production processes were all heavily influenced by the availability of electricity. This indicates that spinning machines are powered by electricity and that a steady supply provides optimal performance and production.

Water availability had a significant impact on the spinning, weaving, finishing, and garment manufacturing processes. This suggests that water is used to wash and treat fibers before spinning, which has an impact on the cleanliness and quality of the finished yarn.

The adjustment coefficients C(1), C(12), C(23), and C(34) were significant, indicating a LR connection in Table 6. There is a short-term causal relationship between garment and finishing, finishing with weaving, weaving with spinning, and spinning with its lag.

Adjustment coefficients	Coefficient	Standard error	t-Statistic	Probability
C(1)	-0.43	0.06	-7.15	0.0000
C(12)	-2.33	0.44	-5.35	0.0000
C(23)	-0.84	0.30	2.85	0.0296
C(34)	-0.22	0.09	-2.32	0.0208

TABLE 6: Least square estimation

Model checking

Portmanteau Q-statistics and the Lagrange multiplier test for VECM residual serial correlation results revealed no significant residual autocorrelation problem up to lag 12, with all p-values beyond the 0.05 level of significance in Table 7. The results of the separate Jarque-Bera series demonstrated multivariate residual normality, as the p-values for spinning; weaving, finishing, and garment were 0.5231, 0.8375, 0.3121, and 0.7666, respectively. The autoregressive conditional heteroscedasticity test findings showed that there was no significant evidence of ARCH (p-value is 0.9302).

Structural analysis

The findings of the pairwise Granger causality tests demonstrated that spinning Granger causes weaving, finishing, and garment, but the reverse was not true. This means that changes in spinning occur before changes in weaving, finishing, and garment and that the most recent information on spinning can be used to forecast the future value of weaving, finishing, and garment.

According to the impulsive reaction, applying a shock to spinning, weaving, finishing, and the garment had a positive impact on the garment. Figure 1 presents an impulsive reaction on the fourth box; a one standard deviation (SD) shock (innovation) in the garment had a declining impact on the garment up to two periods later and then an increasing impact from the second to the third period. After the third period, the garment fails. Furthermore, shocks on spinning (within one SD) showed a diminishing effect on the garment from periods 1 to 3 and an increasing impact from 3 to 4. Beyond the fourth period, it achieves a steady state value and continues in the positive range. This implies that spinning shocks had a positive impact on garment performance in short run (SR) and LR.

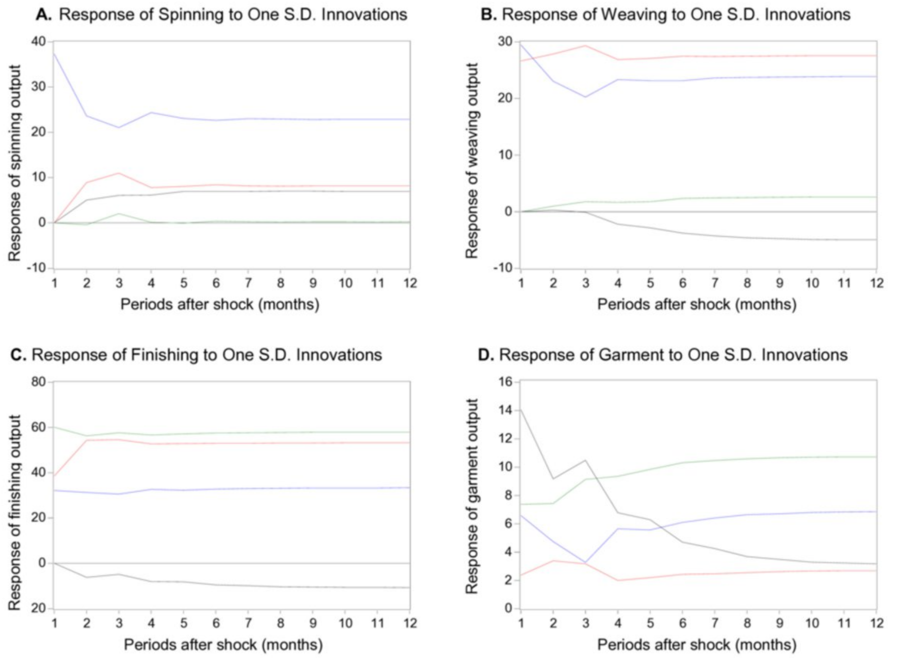

FIGURE 1: Graphs of the Impulse Response Function. (A) represents the response of Spinning to one S.D. innovation, (B) represents the response of Weaving, (C) represents the response of Finishing, and (D) represents the response of Garment to one S.D. innovation

The colored lines indicate different production outputs: Blue Line – Spanning Output; Red Line – Weaving Output; Green Line – Finishing Output; lack Line – Garment Output

Forecast and evaluation of accuracy

The result of 12 months was picked, and 100% of the forecast error variance of spinning was explained by itself, implying that other factors in the model did not influence the first month. In the second month, 94.9% of the variability in the spinning fluctuation was explained by its invention, with the other variables accounting for only 6.1%, indicating that they had little influence in predicting future spinning values in the SR. The fraction of spinning's influence on itself increases in the following months, reaching 84.76% after 12 months, and it continues to have a significant influence on itself throughout time. After 12 months, weaving accounts for 9.42% of total contribution, garments for 5.8%, and finishing for 0.6%. In the LR, however, other variables have little influence on future spinning values.

Similarly, the table and figure findings revealed that in the first month, 45% of the forecast variance decomposition of the weaving was explained by itself, and the influence of weaving in predicting its future value itself increased to 56.4% after 12 months in the LR period. Furthermore, as proven, spinning had a substantial impact on predicting future weaving values in both the short and long term. However, finishing and garment had almost no effect on weaving in both the SR and LR times.

For finishing, the forecast variance breakdown explained by itself in the first month was around 58.8%, followed by 35% in the 12 months. This shows that completion has a significant impact on predicting future values in the short term but minimal impact in the long term. However, weaving innovation increased by 24% in the first month and 37% in the 12 months, spinning by 16% and 14%, and garments by 0% and 1.1%, respectively. As a result, weaving had an impact on predicting future finishing value in both the short and long term.

For the garment, the prediction variance breakdown explained by its own variation was 65.7% in the first month and 25.3% over 12 months, demonstrating that the garment had a significant impact on predicting its own future value in the short term. However, finishing had a 51.2% influence on forecasting clothes over 12 months, weaving 3.6%, and spinning 19%. This shows that finishing has a significant impact on estimating the future value of the garment.

The fitted model's forecasting accuracy was checked before producing a forecast for 2024, yielding a oneyear head forecast. The Residual Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE) values were less than 5%, and the Theil-U statistic was close to zero, implying that the discrepancy between actual and predicted values was minor in Table *8*.

Discussion

According to the correlation matrix between dependent variables revealed that almost all variables were strongly connected. The manufacturing function's quality assurance procedures, as well as its capacity to deliver a quality product/service, were found to have a strong relationship with firm performance. According to country data, Ethiopia has only 40% of the required resources on hand, with the remaining 60% imported [13]. The relationship between independent variables revealed that almost all variables were substantially associated, even though some elements, such as employees, were poorly correlated with all other variables. In contrast to previous research, production and services have a high impact on the success of textile firms [14]. Other research in terms of the four primary performance factors of quality, cost, productivity, and time indicated that supply chain performance in Ethiopia's textile sector is regarded moderate [18].

As a result, indicating that all series were non-stationary at level but stationary at first difference. This is the same as [24,25,35]. The adjustment factors for garments, finishing, weaving, and spinning were -0.43, -0.33, -0.84, and -0.22, respectively. In comparison to a study conducted in Nigeria, it was discovered that whereas labor force had a positive LR association with manufacturing value added, average manufacturing capacity utilization had a negative LR relationship [22]. The other found a favorable LR link between the manufacturing sector, GDP, and employment [23].

The number of mechanics had a significant impact on the spinning and garment manufacturing processes. In comparison to other studies, it had been noticed in Addis Abeba that many garment companies are unable to fulfill their overheads and so are not profitable because the machines were laying idle [1]. The volume of air supply had a big impact on the garment production process. The spinning, weaving, finishing, and garment production processes were all heavily influenced by the availability of electricity. In comparison, studies found that a lack of power looms and government funding were slowing the expansion of the textile industry in Vietnam, India, and Pakistan [7]. This issue is mostly caused by inadequate processes and a lack of education among workers [9]. A study in Taiwan using an artificial neural network found that industrial power demand is price inelastic or has a negative value of -0.17 to -0.23, with climate change favorably impacting energy demand [20].

Water availability influences every stage of textile production, but it is most critical in the finishing stage due to the high-water demand for processes like dyeing, bleaching, and washing. Other research indicates that there is a long sequence of wet processing phases that require the input of water, chemicals, and energy while producing waste at each level [6]. There is a short-term causal relationship between garment and finishing, finishing with weaving, weaving with spinning, and spinning with its lag. In comparison, other study findings revealed that there were no SR associations between the variables [23].

The study's dependence solely on secondary data limits it, as it may add biases and unresolved measurement difficulties. The study makes use of VAR models, which are suitable for investigating dynamic relationships in time series data. While the statistical findings reveal predictive correlations and shock spread, operational concerns and infrastructure consequences may benefit from more direct evidence or contextual research rather than depending solely on model-based conclusions. Furthermore, little consideration is given to potential external impacts affecting the textile industry, such as market dynamics or regulatory changes.

Conclusions

This study examined the dynamic interrelationships among key sub-sectors of the textile industry-spinning, weaving, finishing, and garments-using a VAR model. Upon establishing the presence of cointegration among the variables, the VECM was applied to capture both short-term fluctuations and long-term equilibrium behavior.

The empirical findings revealed notable differences in the speed at which each sub-sector adjusts to deviations from LR equilibrium. Adjustment coefficients for garments, finishing, weaving, and spinning were estimated at -0.43, -0.33, -0.84, and -0.22, respectively. These results indicate that the weaving sub-sector demonstrates the highest level of responsiveness, correcting approximately 84% of disequilibrium per period, followed by garments (43%), finishing (33%), and spinning (22%). Such disparities suggest that while all sub-sectors are responsive to long-term imbalances, the magnitude and pace of adjustment differ substantially.

Additionally, the study identified significant operational challenges impacting textile production. Mechanical failures were particularly disruptive to spinning and garment operations. Inadequate air supply negatively affected garment manufacturing, while power shortages and limited water availability had adverse effects across all four sub-sectors, impeding both efficiency and output quality.

These findings highlight the necessity for integrated and well-coordinated policy interventions, supported by strategic investments to upgrade infrastructure, ensure consistent utility services, and enhance maintenance systems. Addressing these foundational issues will allow stakeholders to boost the textile industry's operational efficiency, long-term stability, and global competitiveness. Furthermore, using renewable energy is consistent with global sustainability goals and can improve the company's environmental reputation, thereby opening the door to greener markets and incentives. Future research could focus on international comparisons, long-term facility studies, implementation of improvements, technology adoption, and workforce training to strengthen the textile sector's ability to withstand external challenges.

Appendices

Lag	Q-stat		Adj Q-stat		LM-Stat	
	Value	Prob.	Value	Prob.	Value	Prob.
1	9.985133	0.8674	10.07048	0.8629	43.69440	0.9137
2	38.74858	0.1914	39.32985	0.1746	30.83213	0.4497
3	64.81583	0.0531	66.07711	0.0427	27.64385	0.3692
4	80.58017	0.0788	82.39459	0.0606	16.75272	0.9371
5	95.74356	0.1106	98.22892	0.0814	18.67092	0.9866
6	111.1848	0.1378	114.4974	0.0959	15.89098	0.9853
7	135.3733	0.0657	140.2113	1.0000	27.03078	0.9916
8	151.4734	0.0768	157.4823	1.0000	17.58986	0.9791
9	75.73525	0.9998	82.15976	0.9986	25.07648	0.0685
10	81.26960	1.0000	88.47359	0.9998	5.704629	0.9910
11	94.42127	1.0000	103.6920	0.9996	13.22808	0.6560
12	170.9926	0.5074	193.5800	0.1243	106.7710	0.0700

TABLE 7: Test of residual autocorrelation

Variables	RMSE	MAE	MAPE	Theil-U statistic
Spinning	33.89	30.52	5.86	0.03
Weaving	183.65	120.77	11.11	0.08
Finishing	28.89	23.14	6.50	0.04
Garment	32.41	26.00	6.99	0.04

TABLE 8: Forecasting accuracy

RMSE, Residual Mean Square Error; MAE, Mean Absolute Error; MAPE, Mean Absolute Percentage Error

Additional Information

Author Contributions

All authors have reviewed the final version to be published and agreed to be accountable for all aspects of the work.

Concept and design: Tegenu Tento, Sitotaw Ahmed

Acquisition, analysis, or interpretation of data: Tegenu Tento, Sitotaw Ahmed

Drafting of the manuscript: Tegenu Tento, Sitotaw Ahmed

Critical review of the manuscript for important intellectual content: Tegenu Tento, Sitotaw Ahmed

Supervision: Tegenu Tento

Disclosures

Human subjects: All authors have confirmed that this study did not involve human participants or tissue. **Animal subjects:** All authors have confirmed that this study did not involve animal subjects or tissue. **Conflicts of interest:** In compliance with the ICMJE uniform disclosure form, all authors declare the following: **Payment/services info:** All authors have declared that no financial support was received from any organization for the submitted work. **Financial relationships:** All authors have declared that they have no financial relationships at present or within the previous three years with any organizations that might have an interest in the submitted work. **Other relationships:** All authors have declared that there are no other relationships or activities that could appear to have influenced the submitted work.

Acknowledgements

The authors would like to express their gratitude to the Bahir Dar textile Share Company for allowing us to use the data analyzed in this study.

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