Impact of Supply Chain Collaboration on the Operational Performance of Textile Enterprises

Xuebin Huang[1], Jianwen Shen[2], Yuhui Chen[1], Biao Zhang[1]
[1]Guangzhou College of Technology and Business, Guangzhou 510850, Guangdong, China
[2]Guangzhou City University of Technology, Guangzhou 510800, Guangdong, China
Corresponding author: Yuhui Chen (e-mail: cyh15800035858@163.com)

ABSTRACT This study investigates the impact mechanism of supply chain collaboration on the operational performance of textile enterprises through a hybrid modeling framework integrating Partial Least Squares Structural Equation Modeling (PLS-SEM) and an Adaptive Neuro-Fuzzy Inference System (ANFIS). A textile-oriented latent variable index system is established to characterize collaboration strength, information sharing degree, and operational performance. The PLS-SEM component is employed to quantify the structural relationships among latent variables, while the ANFIS component captures nonlinear dynamic interactions through a Takagi-Sugeno fuzzy inference mechanism and hybrid learning strategy. Monte Carlo simulation is further introduced to evaluate model robustness and parameter reliability. Experimental results demonstrate that the proposed framework effectively reveals the transmission pathways through which collaborative behaviors influence enterprise performance. When collaboration strength increases from 0.2 to 0.6, inventory turnover optimized by the ANFIS module rises from 1.98 to 2.80, indicating a significant nonlinear response to collaborative activities. The proposed approach provides an effective analytical framework for complex industrial systems characterized by intensive information interaction, dynamic decision processes, and distributed operational structures. The study offers a quantitative methodology for understanding collaboration-driven performance evolution and supports intelligent operational optimization in modern manufacturing environments.

INDEX TERMS supply chain collaboration, operational performance, PLS-SEM, ANFIS

I. INTRODUCTION

THE textile sector faces raw material price volatility, rapidly changing fashion demands, and increasing sustainability requirements in global markets. Supply chain collaboration, a definitive way to optimize corporate competition, materially effects the operational performance of textile firms [1-3]. Operational performance includes the main features of production efficiency, cost management, and on-time delivery rate, and how well it performs directly determines market responsiveness and long-term viability for firms [4,5]. A better understanding of the linkage mechanisms between supply chain collaborations can help textile companies address some vulnerabilities encountered in the industry, such as seasonal demand fluctuations and supply chain disruption risks [6,7]. This work provides a theoretical basis for the industry to achieve efficient resource utilization and help with their green transformation, and it is of both academic value and significance.

Previous research has largely regarded supply chain collaboration as an integrated management practice, overlooking the specificities of the textile supply chain. The supply chain of the textile industry is multilayered, with suppliers, manufacturers, and retailers [8,9]. Moreover, its vulnerabilities arise from the overall sensitivity to raw material pricing, short delivery times, and weather susceptibility. As such, the collaborative behavior has fundamentally unstable properties [10,11]. Due to the seasonality inherent in the textile industry, traditional collaboration models cannot effectively represent dynamic changes in demand forecasting [12,13]. The long time lag of information sharing in the textile supply chain does not help clarify the synergistic influencing factors associated with inventory turnover, thus causing further confusion [14,15]. These constraints limit the textile industry's ability to apply theories developed to create coherent collaboration strategies to enhance business processes. Research has yet to identify the nonlinear dynamics within the textile supply chain, effectively constraining collaboration strategies from any scientific validity. To address the aforementioned challenges, existing research uses SEM (Structural Equation Modeling) to analyze the relationship between collaboration and performance [16,17]. This method requires large sample data, but textile enterprises often face insufficient sample size due to the dispersed nature of their supply chains, leading to biased parameter estimation. OLS (Ordinary Least Squares) is suitable for testing linear relationships [18-20]. However, it cannot handle the nonlinear dynamic characteristics between collaboration strength and operational performance, such as the diminishing marginal effect of information sharing. Some studies have applied fuzzy logic models, but their static rule base [21] is difficult to adapt to the time-varying environment of the textile supply chain. It cannot dynamically adjust the mapping relationship between collaboration variables. Existing methods have failed to effectively integrate the vulnerability characteristics of the textile supply chain, leaving the specific impact path of supply chain collaboration on the operational performance of textile enterprises unclear.

To clarify the impact mechanism of supply chain collaboration on the operational performance of textile enterprises, this paper constructs a hybrid modeling framework based on a cascaded PLS-SEM and ANFIS. Based on the vulnerability characteristics of the textile supply chain, a latent variable index system including collaboration strength, information sharing degree, and operational performance is designed. The iterative algorithm of PLS-SEM is used to minimize the residual variance between the exogenous and endogenous models, estimating the linear path coefficients between latent variables. A module of an ANFIS is integrated, and the nonlinear relationship between collaboration variables and performance indicators is optimally modeled using a Takagi-Sugeno fuzzy rule base and a backpropagation learning algorithm. Lastly, Monte Carlo simulation is employed to generate random samples in order to test the validity of the model. This approach succeeds in accurately analyzing the distinct nonlinear dynamic properties of the textile supply chain, thus providing a theoretical framework for the development of collaboration strategies.

II. HYBRID MODELING APPROACH FOR SUPPLY CHAIN COLLABORATIVE IMPACT MECHANISMS

A. CONSTRUCTION OF LATENT VARIABLE INDICATOR SYSTEM

A latent variable indicator system reflecting industry-specific traits is developed for textile supply chains [22,23]. The system has three latent variables: collaboration strength, information sharing degree, and operational performance, and each is made up of measurable indicators. Collaboration activity is quantified through the frequency of order sharing and the number of joint planning meetings, representing the operational level of inter-organizational interaction within the textile supply chain. This metric captures the tangible manifestations of collaborative behavior through the ratio of shared orders to total order processing and the frequency of collaborative planning sessions relative to maximum possible meeting days. The degree to which information is shared is expressed by the number of system connections, data exchanges, and the timeliness of updates to the information. The number of system connections refers to the number of direct system connections among the various upstream and downstream enterprises in the chain. The data exchange frequency refers to the number of data transmissions at each node of the supply chain per unit time. Information update timeliness refers to the time interval between data generation and downstream acquisition.

Operational performance integrates production efficiency, inventory turnover rate, and on-time delivery rate. Confirmatory factor analysis was performed to validate the construct validity of the operational performance latent variable. The results showed factor loadings ranging from 0.72 to 0.85 with composite reliability of 0.87 and average variance extracted of 0.61. Discriminant validity was established through the Fornell-Larcker criterion where the square root of AVE (0.78) exceeded inter-construct correlations. These statistical validations confirm the three indicators form a coherent operational performance construct specific to textile supply chain context. Production efficiency refers to the ratio of actual output per unit time to standard capacity. Inventory turnover rate refers to the ratio of sales cost to average inventory value over a certain period. On-time delivery rate refers to the ratio of the number of orders delivered on time to the total number of orders.

The expression for quantifying synergy strength is:

$$CS = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{OSF_i}{TOD_i} + \frac{JPM_i}{TMD_i}\right) \tag{1}$$

CS is the intensity of collaboration; n is the number of evaluation periods; OSFi is the number of shared orders in the i-th period; TODi is the total number of orders in the i-th period; JPMi is the number of joint planning meetings in the i-th period; TMDi is the maximum number of days that a meeting can be held in the i-th period.

Information sharing efficiency is evaluated using a weighted approach:

$$ISD = \sum_{j=1}^{3} w_j \cdot x_j \tag{2}$$

ISD represents information sharing degree; wj is the indicator weight coefficient; xj is the standardized value of the indicator; j=1 represents the number of system connections; j=2 represents the data exchange frequency; j=3 represents the timeliness of information updates. The indicator system strictly follows the principle of objectivity to ensure that the measurement results are accurate and reliable.

B. PLS-SEM ITERATIVE CALCULATION AND PATH COEFFICIENT ESTIMATION

PLS-SEM (Partial Least Squares Structural Equation Modeling) can analyze linear associations between latent variables [24,25]. The model input is a latent variable index system, including collaboration strength, information sharing degree, and operational performance. To assist with the algorithm, convergence stability is initiated by treating exogenous and endogenous latent variable weight matrix using unit vector assignments. The iterative computation step using least squares estimates the path coefficients to minimize the residual variances of the exogenous and endogenous variable association paths [26,27]. The latent variable score vector is calculated using the linear combination of the exogenous index variable matrix and the weight vector [28,29].

$$\eta_i = XW_i \tag{3}$$

The weights of the weight vector are updated repeatedly by taking into consideration the covariance structure of the data. The exogenous latent variable weights are calculated based on the correlations between the endogenous latent variable scores and the indicator variables. The path coefficient matrix is estimated using the least squares approach.

$$B = (\eta^T \eta)^{-1} \eta^T \zeta \tag{4}$$

B represents the path coefficient matrix quantifying linear relationships between collaboration strength and operational performance; η denotes the exogenous latent variable score matrix containing standardized measurements of collaboration strength and information sharing degree derived from order sharing frequency and system connection metrics; ζ signifies the endogenous latent variable score matrix representing operational performance metrics including production efficiency, inventory turnover rate, and on-time delivery rate calculated from textile enterprise production data. The iteration termination condition is set as the change in the weight vector between two consecutive iterations being less than 0.001 or reaching the maximum number of iterations (500). To address the issue of insufficient sample size in textile enterprise supply chain data, Bootstrap is used to perform 1000 resampling iterations to construct the virtual sample set required for statistical inference, ensuring the reliability of parameter estimation. After model convergence, standardized path coefficients are output to quantify the linear impact strength of co-variables on operational performance.

C. ANFIS MODULE EMBEDDING AND NONLINEAR RELATIONSHIP OPTIMIZATION

Figure 1 illustrates the collaborative working architecture of PLS-SEM and ANFIS.

Figure 1 presents the architecture of the hybrid modeling method. The PLS-SEM module processes the indicator data of textile enterprises and outputs standardized latent variable scores. The ANFIS module receives input through the feature alignment interface, performs nonlinear optimization through the fuzzy rule layer and hybrid learning algorithm, and finally outputs the analysis results of the supply chain synergy impact mechanism.

The standardized latent variable score vector output by PLS-SEM is used as the input of ANFIS to establish a nonlinear mapping relationship between collaborative strength and information sharing degree to operational performance [30]. The ANFIS module specifically targets the residual nonlinear patterns that remain unexplained after the linear PLS-SEM estimation, modeling higher-order interactions and threshold effects that cannot be captured by linear path coefficients. This residual-focused approach enables the identification of diminishing marginal returns and saturation points in the relationship between collaboration variables and operational performance metrics. The fuzzy rule base dynamically captures nonlinear deviations from the linear structural framework. ANFIS uses a Takagi-Sugeno type fuzzy inference mechanism to construct an initial fuzzy rule base [31-33]. The ANFIS configuration implemented four fuzzy rules derived from grid partitioning with two linguistic terms allocated to each input variable. Gaussian membership functions were selected because their continuous differentiability supports gradient-based parameter optimization and their smooth transition characteristics align with the gradual nature of supply chain collaboration dynamics. Each input variable was discretized into two fuzzy sets representing low and high collaboration states determined through k-means clustering of normalized input data to maintain model interpretability while capturing essential nonlinear patterns.

$$\mu_A(x) = \exp\left(-\frac{(x - c_i)^2}{2\sigma_i^2}\right) \tag{5}$$

$\mu_A(x)$ represents the membership degree of the input variable x to the fuzzy set A; c_i is the membership function center value; σ_i is the membership function width parameter. The network parameters are optimized through a hybrid learning strategy, with linear parameters solved directly using the least squares method and nonlinear parameters adjusted using the gradient descent method [34-35].

The mechanism used to align features maps the PLS-SEM latent variable scores to the ANFIS input space while maintaining the same dimensionality. The error backpropagation procedure uses a hybrid learning algorithm that fixes the nonlinear parameters during forward propagation but allows for the linear parameters to be adjusted during backpropagation. The learning rate is set to 0.01 with a momentum factor of 0.9. This procedure continues iterating until either the change in training error is less than 0.0001 or ten consecutive iterations, or after a maximum number of iterations (1000) has occurred. In this cascaded architecture, the ANFIS module begins to embed the model capture the dynamic behavior of the nonlinear mapping relationships of collaborative variables on operational performance in the textile supply chain.

III. EXPERIMENTAL DESIGN AND RESULTS

A. EXPERIMENTAL SETUP AND DATA ACQUISITION

The experiment is performed on a workstation with an Intel Xeon processor and 64GB memory, running Linux Ubuntu 20.04 LTS. During data preprocessing, the three-standard-deviation rule is used to identify and exclude outliers, and Z-score standardization is applied to each indicator for dimension consistency.

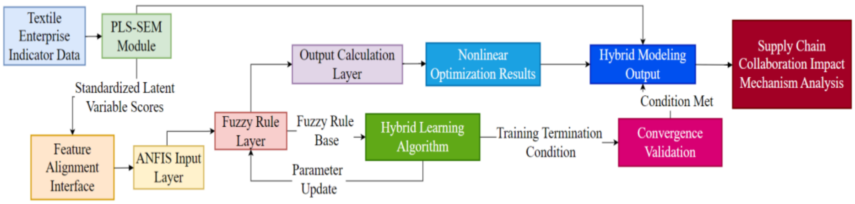

FIGURE 1. Flowchart of hybrid modeling method

TABLE 1. Dataset composition

Sample number	System data coverage time (months)	Data record integrity (%)	Data collection cycle (months)
1	28	92.7	1
2	36	95.3	1
3	19	87.5	1
4	24	91.8	1
5	42	96.2	1
6	26	89.3	3
7	32	94.1	1
8	21	88.7	1
9	38	93.5	1
10	25	90.2	3
11	17	86.9	1
12	31	92.8	1
13	23	90.5	1
14	29	93.2	1
15	34	94.7	1

Table 1 presents the characteristics of sample data from 15 publicly available textile companies; system data ranges from 17-42 months, and the completeness of records in the dataset ranges from 86.9% to 96.2%. Data collection is primarily monthly, with 13 companies using monthly collection and 2 companies using quarterly collection. The hybrid modeling approach demonstrates sufficient robustness through Monte Carlo simulation with 1000 resampling iterations, which compensates for the limited sample size by generating virtual samples for statistical inference. The selected companies represent diverse operational scales and geographic regions within the textile industry, ensuring a broad spectrum of supply chain characteristics. The collaboration strength and information sharing metrics are constructed based on observable order sharing frequencies, joint planning meeting counts, and system connection numbers. Data quality meets the basic requirements of hybrid modeling methods for sample size and completeness, supporting subsequent path coefficient estimation and nonlinear relationship optimization.

B. EMPIRICAL EVIDENCE ON SYNERGISTIC INFLUENCE PATHS

To analyze the impact mechanism of textile supply chain collaboration on operational performance, this study selects five case studies and calculates the standardized path coefficients of collaboration intensity and information sharing degree on operational performance based on a hybrid modeling framework. Collaboration activity quantifies the operational level of inter-enterprise interaction through the frequency of order sharing and joint planning meetings, while information sharing degree assesses supply chain transparency based on the number of system connections, data exchange frequency, and information update timeliness. Together, these two factors constitute the core drivers influencing operational performance. Figure 2 clearly compares the impact intensity of the two types of collaboration elements on operational performance in different samples.

In Figure 2, Sample 5 has a collaboration strength coefficient of 0.86, stemming from its 42-month system data coverage and 96.2% high data integrity, indicating that long-term stable supply chain relationships can effectively enhance collaboration. Sample 6 has the lowest information sharing coefficient at 0.72, due to its quarterly data collection period, which confirms the limiting role of textile supply chain information update timeliness on collaboration effects. Sample 11 has a low collaboration strength coefficient of 0.74 due to its relatively short 17 month period of data coverage, and confirms that lower data quality also reduces the strength of the collaboration effect. These standardized path coefficients derived from PLS-SEM establish the foundational linear relationships between collaboration variables and operational performance, which the ANFIS module subsequently refines by modeling the nonlinear dynamics and threshold effects that emerge as collaboration intensity varies across the textile supply chain, thereby capturing the diminishing marginal returns and saturation points evident in the subsequent nonlinear analysis presented in Figure 4.

C. MANAGEMENT IMPLICATIONS AND STRATEGY SIMULATION

In order to thoroughly assess the hybrid modeling techniques' effectiveness in examining the collaborative mechanisms of the textile supply chain, this work systematically compares the explanatory power and goodness of fit of hybrid modeling with the conventional single PLS-SEM model. The R^2 value is a measure of the model's ability to explain the variation in operational performance; the higher the R^2 value, the more extensive variation in the performance of the textile enterprise was captured. RMSE (Root Mean Square Error) is a measure of the level of divergence between the predicted and actual values; a lower RMSE reflects stronger model stability. Five sample groups are selected for analysis; these achieve diversity in terms of extensive temporal coverage of system data, completeness of data records, and collection cycle – all of which empirically

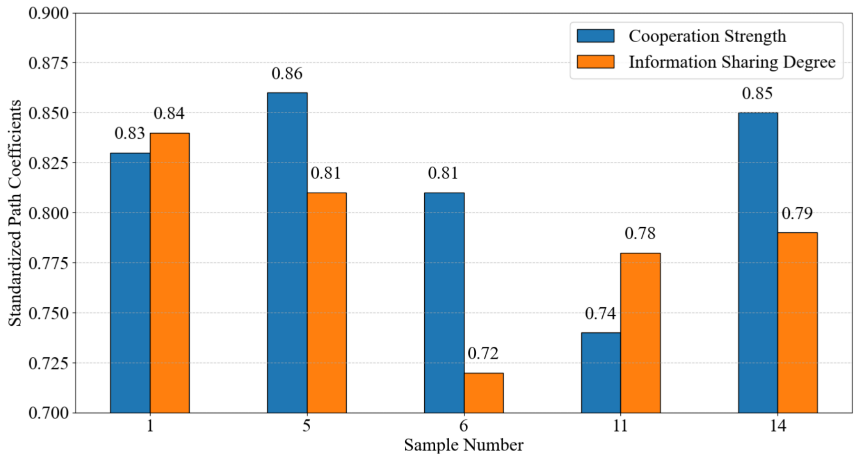

FIGURE 2. Analysis of the differentiated characteristics of the supply chain collaboration path coefficient of textile enterprises

assess the model's ability to adapt under varied data quality conditions. In Figure 3, the left subplot corresponds to the hybrid model incorporating ANFIS, and the right subplot represents the traditional PLS-SEM model.

In Figure 3, the hybrid model performs better across all samples. Sample 5 shows an R^2 value of 0.87 and an RMSE of 0.12, significantly better than the single PLS-SEM model's 0.74 and 0.18. This advantage is particularly evident in samples with high-quality data. Sample 5, with 42 months of system data coverage and a high integrity rate of 96.2%, has a hybrid model R^2 value 0.13 higher than the single model. The impact of the data collection cycle is clearly visible in quarterly collected samples. Samples 10 and 6 have hybrid model R^2 values of 0.75 and 0.67, respectively, still better than the corresponding single models' 0.62 and 0.54. The comparison between Sample 6 and Sample 10 demonstrates the effectiveness of the timeliness constraint on information updates. Sample 6 has slightly less data completeness, resulting in a slightly worse result than Sample 10. Sample 11, as the example with the least data coverage, still produces an overall acceptable R^2 value of 0.66 for the hybrid model, indicating that the ANFIS module can effectively reduce the negative impact of short-cycle data on model performance. The average R^2 value of the hybrid model is 0.75, and the average RMSE is 0.19, best demonstrating that this method can correctly capture the nonlinear dynamic characteristics of the textile supply chain, while overcoming the challenge of insufficient adaptability of traditional models in the presence of gap characteristics.

D. NONLINEAR DYNAMIC EFFECTS AND MODEL ROBUSTNESS TESTING

To examine the nonlinear dynamic characteristics of the textile supply chain collaboration's impact on operational performance, this study applies a hybrid modeling framework using PLS-SEM and ANFIS cascades. The response patterns of inventory turnover and production efficiency are systematically explored as the collaboration intensity varies from 0.2 to 1.0. Collaboration activity quantifies the operational level of interfirm interaction through order sharing frequency and joint planning meeting frequency. Inventory turnover reflects the ratio of sales cost to average inventory value, and production efficiency measures the ratio of actual output per unit time to standard capacity. The three data sources include PLS-SEM linear forecasts, ANFIS nonlinear optimization, and actual observations recorded by the enterprise information system. In Figure 4, when the collaboration strength based on ANFIS nonlinear optimization increases from 0.2 to 0.6, the inventory turnover rate increases from 1.98 to 2.80. Further increases to 1.0 result in an additional increase to 3.18, with the marginal rate of improvement decreasing from 0.82 (1.98-2.80) to 0.38 (2.80-3.18), confirming the diminishing marginal effect of information sharing. The deviation between the ANFIS predicted value and the actual observed value is controlled within ± 0.03, while the PLS-SEM model's predicted value of 3.58 at a collaboration strength of 1.0 is 0.38 higher than the actual value of 3.20. With respect to production efficiency, after the level of collaboration based on the ANFIS nonlinear optimization model reaches 0.6, the efficiency increases from 85.3% to 88.1%, an increase of about 2.8%, showing a similar diminishing marginal effect. This occurs largely due to sensitive raw material prices in the textile industry and the vulnerability of the supply chain stemming from the seasonality of demand. In addition, as the level of collaboration increases, the actual inventory turnover rates decrease from 0.81 (2.01-2.82) to 0.38 (2.82- 3.20), which indicates a slower growth rate. This is also the result of the timeliness issues for either information sharing and increased costs when collaborating at greater levels, which dilutes the performance gains. The ANFIS model, through the Takagi-Sugeno fuzzy rule base, accurately structures dynamic mapping relationships of the textile supply chain, providing a satisfactory basis against the limitations of insufficient adaptability encountered with traditional linear models in a vulnerable environment to address new quantitative strategy on collaboration from textile companies.

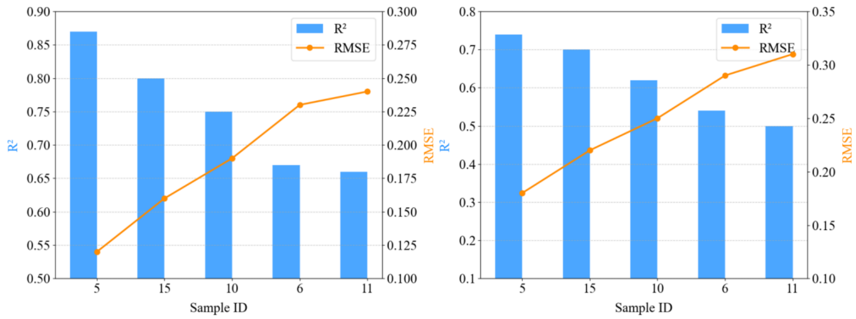

FIGURE 3. Comparative analysis of explanatory power and goodness of fit of the supply chain collaboration model for textile enterprises

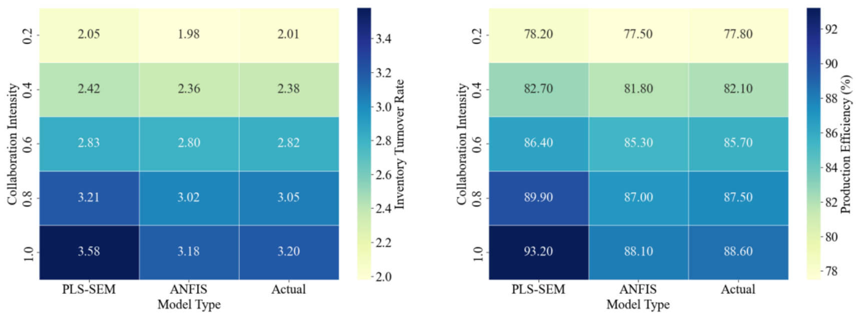

FIGURE 4. Nonlinear impact of synergy intensity on the operating performance of textile enterprises

IV. CONCLUSION

This research integrates cascaded PLS-SEM and ANFIS to characterize collaboration strength, information sharing, and operational performance through a textile-specific latent variable index system. The PLS-SEM module utilizes an iterative calculation for minimizing residual variance as well as obtaining linear path coefficients, while the ANFIS module optimizes nonlinear mapping relationships through a Takagi-Sugeno fuzzy rule base and backpropagation learning mechanism. The analyses reveal a collaboration activity coefficient of 0.86 for Sample 5, and the hybrid model demonstrates an R2 of 0.87 and RMSE of 0.12 for Sample 5. The modeling framework, when collaboration strength is in the range of 0.2 to 0.6, results in the following inventory turnover based on nonlinear optimization through ANFIS: 1.98 and 2.80. With a mean R2 of 0.75 and mean RMSE of 0.19, the hybrid model outperforms traditional methods by capturing nonlinear dynamics in textile supply chain performance related to raw material price fluctuations, seasonal demand shifts, and information delays. This approach provides textile enterprises with a quantitative analysis toolkit for the dynamic transmission path of collaborative mechanisms, effectively addressing the industry specific vulnerabilities and enhancing the ability of enterprises to deal with risks arising from supply chain disruptions.

AUTHOR CONTRIBUTIONS

Conceptualization – Xuebin Huang, Yuhui Chen, Jianwen Shen and Biao Zhang; methodology – Xuebin Huang, Yuhui Chen, Jianwen Shen and Biao Zhang; investigation – Xuebin Huang, Yuhui Chen and Biao Zhang; writing-original draft preparation – Xuebin Huang, Yuhui Chen, Jianwen Shen and Biao Zhang. All authors have read and agreed to the published version of the manuscript.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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