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Process improvement and quality management in the textile industry using Lean Six Sigma methodologies and tools

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ABSTRACT – REZUMAT

Process improvement and quality management in the textile industry using Lean Six Sigma methodologies and tools

An important part of global manufacturing is the textile industry, which produces a wide range of products. In this research, 3 primary textile hubs in Tamil Nadu were selected for data collection: Karur, Tiruppur, and Coimbatore. This study investigates the optimisation of production processes in industry by incorporating the Lean Six Sigma (LSS) methodology. It also examined 5 key theories that addressed crucial issues such as production, defect rates, process inefficiencies, and cycle times. This research also used statistical tools such as Microsoft Excel and Minitab to conduct capacity assessment and process-control defect-rate analysis. This study also used Value Stream Mapping (VSM) and Measurement System Analysis (MSA) for rectifying the above defects. The Lean Six Sigma (LSS) techniques improved productivity in the textile industry by reducing cycle time from 62.5 to 53.1 minutes (15% improvement), lowering defect rates from 19.43% to 12.38% (36.3% improvement), and increasing the sigma level from –3.36 to 0.41 (3.77-unit improvement). The outcomes showed that, when supported by advanced statistical analysis and process mapping, LSS can dramatically boost productivity, product quality, and process reliability in the textile sector.

Keywords: *Lean Six Sigma, textile industry, DMAIC framework, cycle time, defect rate, process optimisation, quality improvement*

Îmbunătățirea proceselor și managementul calității în industria textilă utilizând metodologii și instrumente Lean Six Sigma

O parte importantă a producției globale la nivel mondial este industria textilă, care realizează o gamă largă de produse. În cadrul acestei cercetări, au fost selectate cele trei centre textile principale din Tamil Nadu pentru colectarea datelor, și anume Karur, Tiruppur și Coimbatore. Acest studiu investighează optimizarea proceselor de producție din industrie prin încorporarea metodologiei Lean Six Sigma (LSS). De asemenea, au fost analizate 5 teorii importante care abordează aspecte cruciale precum producția, ratele defectelor, ineficiențele proceselor și duratele ciclurilor. Această cercetare a utilizat, de asemenea, instrumente statistice precum Microsoft Excel și Minitab pentru a determina evaluarea capacității și analiza ratei de defectare a controlului proceselor. Acest studiu a utilizat, de asemenea, Cartografierea Fluxului de Valoare (VSM) și Analiza Sistemului de Măsurare (MSA) pentru remedierea defectelor menționate mai sus. Tehnicile Lean Six Sigma (LSS) au îmbunătățit productivitatea în industria textilă prin reducerea duratei ciclului de la 62,5 la 53,1 minute (îmbunătățire de 15%), scăderea ratelor defectelor de la 19,43% la 12,38% (îmbunătățire de 36,3%) și creșterea nivelului sigma de la –3,36 la 0,41 (îmbunătățire de 3,77 unități). Rezultatele au examinat modul în care, atunci când este susținut de analize statistice avansate și cartografierea proceselor, LSS poate crește semnificativ productivitatea, calitatea produselor și fiabilitatea proceselor în sectorul textil.

Cuvinte-cheie*: Lean Six Sigma, industria textilă, cadrul DMAIC, durata ciclului, rata defectelor, optimizarea proceselor, îmbunătățirea calității*

INTRODUCTION

The goal of lean manufacturing in the textile sector is to maximise customer value by reducing waste and increasing productivity at every stage of production. By implementing Lean principles, textile manufacturers hope to reduce excess inventory, streamline processes, and eliminate non-value-added activities. This led to faster delivery, lower costs, and better quality. Kaizen, Just-in-Time (JIT), Total Productive Maintenance (TPM), and Value Stream Mapping (VSM) are among the primary Lean tools used in the textile industry. Businesses can use value stream mapping to see the entire production process, from acquiring raw materials to shipping the finished product, and identify inefficiencies such as lengthy wait times and transportation bottlenecks. Just-in-time (JIT) production methods ensure materials and products are produced only when needed by preventing overproduction and reducing the need for large inventories. A more responsive production environment results in lower storage costs and better cash flow.

In the textile industry, where delivery schedules and notable variations in product demand are commonplace, lean manufacturing has become increasingly important. Lean emphasises employee involvement and continuous improvement to foster a culture of problem-solving and waste reduction at all organisational levels. One of the main advantages of lean manufacturing is its capacity to increase product quality while reducing production costs. In lean approaches, tools such as Total Quality Management (TQM) and Six Sigma are frequently used to improve defect prevention and reduce process variability. Furthermore, lean manufacturing gives textile companies greater flexibility, allowing them to respond more skillfully to shifting market trends and consumer preferences. At last, implementing lean techniques makes the textile sector more competitive in a fast-moving global marketplace, enhances customer satisfaction, and builds more sustainable operations. Figure 1 depicts the types of apparel.

Fig. 1. Apparel types

In the textile industry, lean manufacturing is increasingly used to increase productivity, reduce waste, and improve efficiency. Its adoption can be facilitated by a structured framework that helps textile manufacturers improve operational performance and product quality while systematically eliminating non-value-added activities. Understanding the different lean tools and practices, such as value stream mapping, 5S, and continuous improvement, is a major challenge. All organisational levels must be committed to the implementation for it to be successful, with a focus on staff training and involvement. Manufacturers can improve their competitiveness, streamline operations, and reduce operating costs by focusing on waste reduction and workflow optimisation. This will result in long-term success and sustainable growth in the textile industry [1]. To promote a more sustainable production process, green lean production in the textile sector seeks to combine lean manufacturing concepts with environmental sustainability. To assess the effectiveness of green lean production, a hybrid fuzzy decision-making framework that accounts for both environmental and economic factors has been developed. In addition to increasing operational efficiency, this strategy helps textile companies identify and implement eco-friendly practices such as waste minimisation, water conservation, and energy conservation. Fuzzy logic is utilised in the decision-making process to account for environmental uncertainty, providing a framework that is adaptable and flexible enough to be customised for various organisational contexts. This framework's implementation promotes the development of an eco-friendly, sustainable, and productive production environment in the textile sector, supporting the sector's overall environmental responsibility [2].

Several obstacles could prevent the textile industry from successfully implementing lean principles. Organisational culture, inadequate training, change aversion and the difficulty of integrating lean practices with current procedures are frequently the causes of these challenges. Adopting lean strategies is further complicated by the textile industry's reliance on manual labour and antiquated technologies. Overcoming these obstacles requires an all-encompassing strategy that aligns lean practices with business goals, fosters strong leadership, and engages employees. To successfully implement lean, which eventually boosts output quality and customer satisfaction in the textile industry, these obstacles must be recognised and removed [3]. The apparel industry in Bangladesh has been greatly impacted by lean manufacturing, which has been used to improve operational performance. The adoption of lean methods, such as cutting waste, shortening lead times, and improving process flow, has improved resource utilisation and reduced costs. Research in the clothing industry shows that businesses that use lean manufacturing report higher profitability, productivity, and efficiency. Additionally, because the emphasis on collaboration and ongoing improvement fosters a positive corporate culture, lean practices have been linked to higher employee satisfaction. However, to ensure the long-term viability of lean initiatives in the apparel industry, issues such as supply chain disruptions and fluctuating demand need to be carefully managed [4].

Six Sigma techniques have been successfully applied in the textile industry to improve productivity and quality. A case study illustrated how operational processes were significantly improved by fusing the lean concepts with Six Sigma's emphasis on minimising variation. This strategy reduces errors and increases customer satisfaction by addressing both product quality consistency and production process efficiency. Organisations can streamline processes, improve efficiency, and produce high-quality goods at competitive prices by implementing Lean Six Sigma, which emphasises data-driven decision-making and strict process control [5]. Using lean manufacturing techniques has greatly improved the textile industry's operational performance. Waste reduction, production process optimisation, and continuous improvement are examples of lean practices that have been shown to lower costs and boost overall productivity in textile manufacturing operations. Industry data indicate that businesses that use lean manufacturing experience improvements in key performance metrics, including lead time, production costs, and product quality. Furthermore, the emphasis on employee empowerment and engagement in lean manufacturing fosters an innovative, problem-solving culture that supports textile companies' long-term competitiveness and success [6]. One of the main goals in enhancing operational effectiveness and environmental sustainability in the textile sector has been to develop a waste-reduction model based on lean manufacturing principles. Businesses can significantly lower their operational costs and environmental impact by implementing lean strategies, such as reducing material waste, using less energy, and streamlining production processes. This strategy not only increases output but also fits in with the textile industry's growing focus on sustainability.

Businesses that use lean manufacturing to reduce waste are better positioned to meet consumer demand for eco-friendly products and regulatory requirements, resulting in a more sustainable and lucrative future [7].

With a focus on the sewing sector, a lean manufacturing model based on production management has been suggested for small textile businesses to increase efficiency and reduce waste. By focusing on the sewing department, which frequently encounters bottlenecks in small textile businesses, the model seeks to improve productivity, reduce operating expenses, and streamline processes. By putting this lean model into practice, small textile businesses could become much more profitable and competitive, helping them compete in a fast-moving market [8]. Changes in consumer demand, workforce management and supply chain disruptions are just a few of the major issues the COVID-19 pandemic has brought about for the textile sector. An integrated approach to examining the obstacles to lean manufacturing in this setting emphasises the necessity of a flexible and robust supply chain, the importance of preserving worker safety, and the role technology plays in facilitating remote work and production processes. The importance of sustainability in manufacturing has been highlighted by the pandemic, which has led textile companies to prioritise both long-term environmental responsibility and operational efficiency. By addressing these issues, textile companies can overcome obstacles to lean implementation and emerge stronger in the post-COVID world. One important element in enhancing operational agility during the COVID-19 era in the textile industry has been the combination of lean practices and quick-response manufacturing. Textile companies have been better equipped to adapt to shifting demand patterns and pandemic-driven supply chain disruptions by combining the flexibility and speed of quick-response manufacturing with the waste-reduction principles of lean manufacturing. This strategy gives businesses a competitive edge in a rapidly changing market by enabling them to shorten lead times, manage inventory more effectively, and increase overall production efficiency. However, to prevent potential problems such as overproduction or more complex production systems, combining these practices requires careful planning and coordination [9].

In the textile industry, lean layout design is essential for increasing the productivity of production processes. A textile manufacturing facility's layout was redesigned in a case study using lean principles, with an emphasis on increasing worker productivity, reducing movement waste, and optimising material flow. The company shortened lead times, increased operational efficiency, and improved overall product quality by rearranging the layout to facilitate a steady, uninterrupted flow of materials. The lean layout design enhances operational and employee well-being by promoting a safer, more ergonomic workplace and increasing production efficiency [10]. Estimates of the effectiveness and growth of lean production in textile companies indicate substantial advantages, including lower costs, higher quality, and increased output. By reducing waste, optimising workflows, and increasing resource utilisation, applying lean principles streamlines operations.

Additionally, the emphasis on employee involvement and ongoing improvement fosters an innovative and efficient culture in textile businesses. The predicted effects of lean production underscore its potential to enable more profitable, efficient, and sustainable manufacturing processes as the sector further develops, positioning textile companies for long-term success [11].

In fact, textile companies can achieve greater efficiency, customer satisfaction, and competitive advantage in a demanding global market by using this integrated approach [12]. A model focusing on optimising waste-reduction processes and standardising work practices is proposed to enhance productivity in the textile industry by applying lean manufacturing techniques. The model highlights the importance of aligning lean concepts with the specific requirements and features of the textile sector to ensure that implemented practices are suited to the challenges faced by textile producers. Lower production costs, higher-quality products, and increased operational efficiency are the anticipated results of implementing this model. Textile companies can greatly increase their productivity and profitability in the market by strategically implementing lean techniques [13]. Productivity and layout design in the sewing portion of the apparel industry have been significantly impacted by lean manufacturing. An analysis of the effects of lean methods in this field emphasises the significance of resource efficiency, waste reduction, and process optimisation. Redesigning the layout and implementing lean techniques such as value stream mapping and standardised work can help clothing manufacturers reduce cycle times, improve quality, and increase overall productivity. In addition to improving operational performance, the adoption of lean manufacturing by the sewing sections promotes employee collaboration and a culture of continuous improvement, which boosts productivity and competitiveness over the long run [14].

METHODOLOGY

Data collection and demographic analysis

The three main textile manufacturing centres in Tamil Nadu were the focus of the study's extensive data collection strategy: Coimbatore, Tiruppur, and Karur. These areas were selected for their diverse operational profiles and significant contributions to the textile industry. Overall, 300 product quality evaluations focused on defect rates, production durations, and resource usage were included in the data, along with 500 process observations covering different production stages. An analysis of the manufacturing units' attributes, such as their size small, medium and large, the number of employees, product types such as apparel, home textiles and technical textiles, and yearly production volume was conducted using demographic profiling in table 1. The demographic data supplied important background information for interpreting differences in process performance and quality metrics.

Data analysis tool

In this study, Minitab and Microsoft Excel were essential for statistical analysis and process control in textile manufacturing. Minitab was used for advanced data analysis [15], including capacity assessment, sigma level estimation, and Statistical Process Control (SPC), employing control charts ($\overline{X}$-R, I-MR), capability histograms, and Pareto analysis to monitor defect rates and process variation. It also facilitated hypothesis testing (ANOVA, t-tests, chi-square) and regression analysis to identify inefficiencies. Microsoft Excel, on the other hand, was used for data aggregation, preprocessing, and visualisation through trend analysis, scatter plots, bar charts, and pivot tables. It computed statistical metrics such as mean, standard deviation, and correlation coefficients, and used conditional formatting to highlight defects and cycle-time variations.

The solver tool was applied for preliminary optimisation, improving efficiency by adjusting operational parameters. The integration of Minitab for statistical validation and Excel for data handling ensured a comprehensive, data-driven approach to process improvement, optimising quality and productivity in textile manufacturing. Utilising sophisticated instruments such as Value Stream Mapping (VSM), inefficiencies throughout the production process were identified [16, 17]. Key performance metrics such as cycle time, sigma levels, and defect percentages were validated, and data reliability was evaluated using measurement system analysis (MSA).

Proposed methodology

The suggested approach for applying Lean Six Sigma (LSS) in the textile industry, adhering to the DMAIC framework, is shown in figure 2.

Critical-to-quality (CTQ) factors, including cycle time, defect rates, and production efficiency, were the focus of stakeholder consultations and process mapping using SIPOC diagrams to establish project objectives during the Define phase. A total of 300 product quality evaluations and 500 process observations from textile units in Coimbatore, Tiruppur, and Karur were used to gather data for the Measure

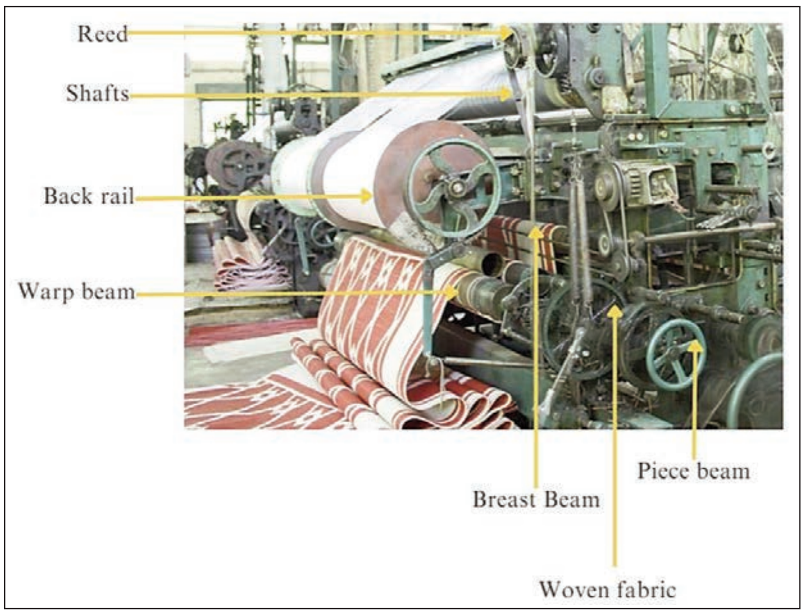

Fig. 2. LSS in the textile sector

Table 1

DEMOGRAPHIC PROFILES								
Region	**No. of units surveyed**	**Employee range**	**Annual output (tons)**	**Primary products**	**Process observations**	**Product quality assessments**	**Product evaluated**	**Processes**
Coimbatore	10	50–200	1,200	apparel, yarn	200	100	cotton shirts	handling, weaving/knitting, dyeing, cutting, sewing, finishing, and packaging
Tiruppur	12	100–300	1,800	knitwear, hosiery	180	120	T-shirts, innerwear	
Karur	8	30–150	900	home textiles, fabrics	120	80	bedsheets, towels	

phase. When initial metrics were assessed, they showed a defect rate of 19.43%, a sigma level of –3.36, and an average cycle time of 62.5 minutes. The DMAIC architecture is shown in figure 3.

In the Improve phase, the improvement strategies centred on retraining staff on quality control standards, implementing preventive maintenance schedules for machinery, and optimising production layouts to reduce material transportation time. Before these changes were fully implemented, pilot projects and simulations were conducted to validate them. Ultimately, a systematic control plan was created during the Control phase, which included employee incentive programs, recurring audits, and real-time monitoring dashboards to ensure sustainability and sustain the gains. This comprehensive strategy guarantees a strong, scalable framework for increasing output and quality in the textile sector.

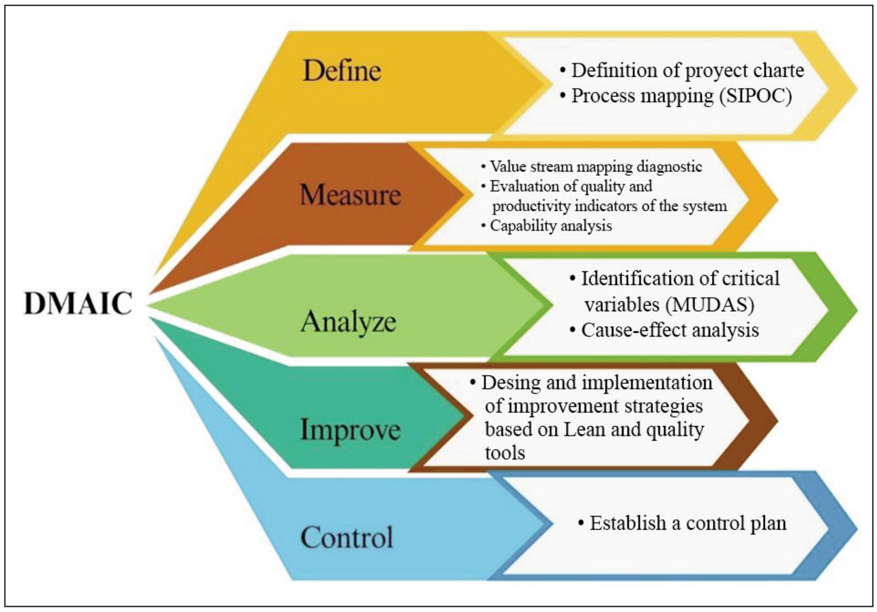

Fig. 3. DMAIC framework

Hypothesis testing

The study investigates key factors affecting manufacturing efficiency and product quality, focusing on defect rates, production cycle time, and process optimisation. Elevated defect rates indicate that product quality does not meet industry standards, which may result from inconsistencies in raw materials, inadequate process control, or equipment inefficiencies. Additionally, significant deviations in production cycle time suggest operational inefficiencies, potentially caused by bottlenecks, unoptimized workflows, or machine downtime. The presence of such inefficiencies, coupled with variations in raw materials, contributes to increased defect rates and overall production challenges. Implementing Lean Six Sigma methodologies can address these issues by identifying root causes, optimising workflows, and standardising processes, thereby reducing defects and improving cycle time. Furthermore, sustaining these improvements through robust control measures ensures long-term operational efficiency and consistent product quality, ultimately aligning manufacturing performance with industry benchmarks.

H_1: The defect rate exceeds industry standards, impacting product quality.

H_2: The production cycle time deviates significantly from the target, indicating inefficiencies.

H_3: Process inefficiencies and raw material variability drive high defect rates.

H_4: Lean Six Sigma tools will reduce cycle time and improve product quality.

H_5: Control measures will sustain improvements in efficiency and quality.

RESULTS AND DISCUSSION

Define phase

H_1: The defect rate exceeds industry standards, impacting product quality.

Figure 4 presents an integrated framework for the manufacturing process of sports sweaters, outlining the supply chain, inputs, processes, outputs, and customer segments. The supply section involves providers, supply chain management, maintenance management, human resources management, financial management, and marketing management to ensure seamless operations. In the input stage, essential resources such as workers, machinery, equipment, information systems, work orders, and textile materials are consolidated for efficient production. The process phase encompasses critical activities such as picking, cutting, assembly, and packing, all of which contribute to producing high-quality clothes of all types. The output stage delivers manufactured garments, along with release orders and bills of sale, to document and facilitate transactions. Lastly, the customer section focuses on distribution, financial management, customer service, and catering to corporate and individual clients, ensuring comprehensive service and satisfaction. This interconnected system ensures a streamlined and efficient manufacturing workflow, promoting quality and customer-centric outcomes.

Table 2 presents an analysis of the Define phase for Hypothesis 1, focusing on initial defect rates, cycle times, and observations across three regions: Coimbatore, Tiruppur, and Karur. This study identifies defects in textile products, including stitching issues (skipped stitches, seam puckering), colour inconsistencies (shade variation, fading), fabric flaws (holes, knots, wrinkles), and finishing problems (loose threads, uneven trims). Cycle time is the total duration of production, including raw material processing, cutting, sewing, dyeing, printing, and packaging.

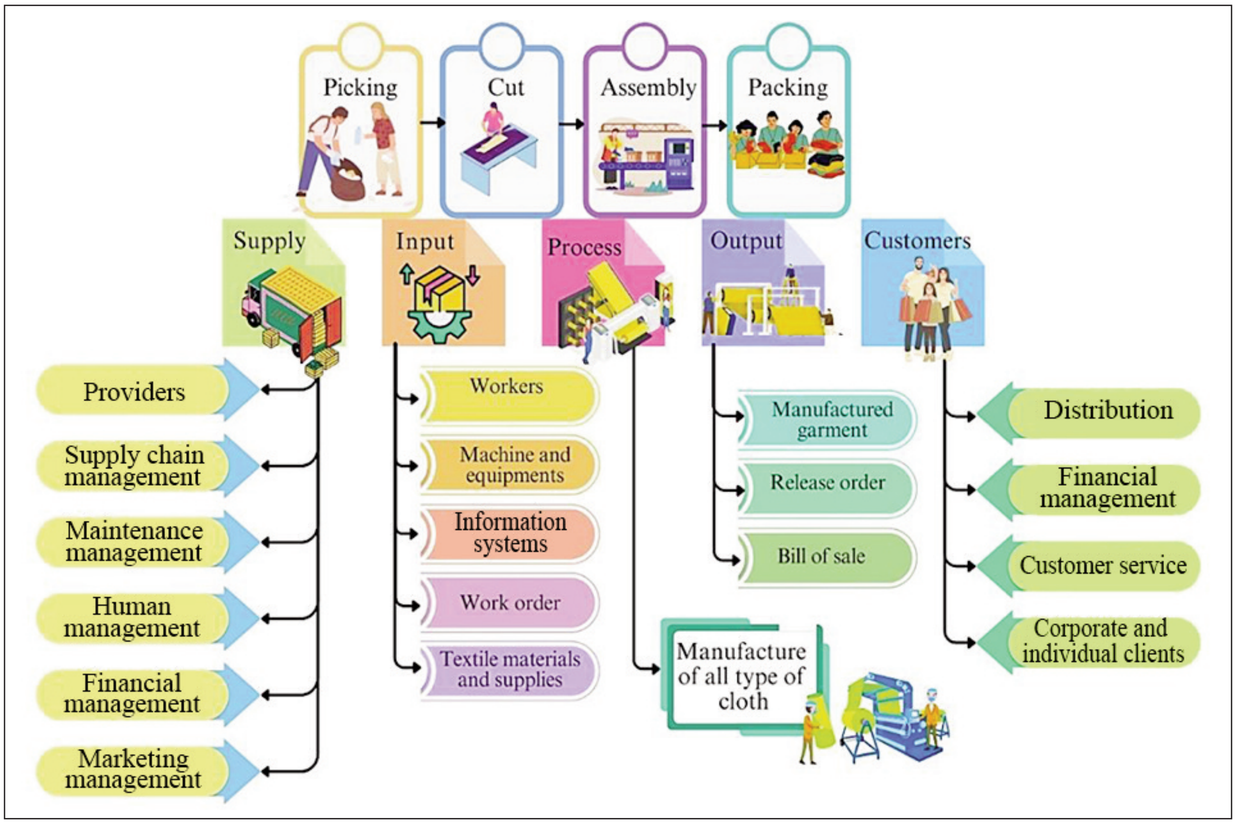

Fig. 4. SIPOC diagram for garment manufacturing in the textile industry

Table 2

ANALYSIS OF DEFINE PHASE (HYPOTHESIS 1)				
Parameter	**Region**	**Observation count**	**Defect rate (%)**	**Cycle time (minutes)**
Initial defect rate	Coimbatore	100	20.1	64.2
	Tiruppur	80	19.2	61.8
	Karur	70	18.6	60.4
Benchmark defect rate	-	-	10.0	50.0

Observations involve real-time monitoring of production lines to detect inefficiencies, bottlenecks, and quality variations.

Coimbatore recorded the highest observation count at 100, with an initial defect rate of 20.1% and a cycle time of 64.2 minutes. Tiruppur followed with 80 observations, a defect rate of 19.2%, and a cycle time of 61.8 minutes. Karur, with 70 observations, showed the lowest defect rate at 18.6% and the shortest cycle time of 60.4 minutes. These figures are compared against a benchmark defect rate of 10.0% and a cycle time of 50.0 minutes, highlighting the gap between current performance and the desired standard across all regions. This analysis underscores the need for process improvements to align with benchmark metrics.

Measure phase

H_2: The production cycle time deviates significantly from the target, indicating inefficiencies.

Figure 5 compares initial cycle time (CT) performance with the new process status after implementing improvements. The data is represented using a histogram overlaid with a probability density curve and trend line. This study applied Lean Six Sigma improvements, including process optimisation using Value Stream Mapping (VSM), preventive maintenance, employee training, defect reduction through Statistical Process Control (SPC), and workstation layout modifications. These strategies minimised downtime, reduced defects, streamlined workflows, and enhanced production efficiency. The initial performance shows greater variability and higher CT values, whereas the post-improvement results exhibit a more concentrated distribution around the optimised CT range. The probability density curve peaks near the target mean CT, signifying a significant reduction in deviation and enhanced consistency. This visual evidence confirms the effectiveness of process improvements in achieving streamlined, efficient operational performance.

Table 3 presents an analysis of the Measure phase for Hypothesis 2, evaluating cycle time and sigma

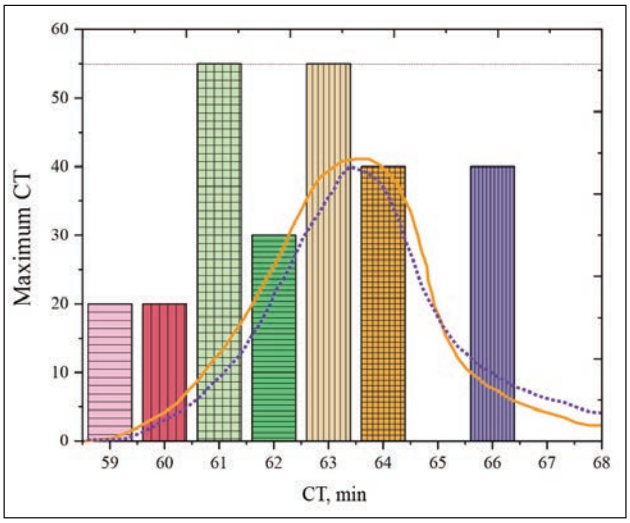

Fig. 5. Cutting accuracy and quality control measures

level across regions using statistical metrics. In Coimbatore, the mean cycle time was 64.2 minutes, with a standard deviation of 5.2, and a 95% confidence interval of 63.1 to 65.3 minutes. Tiruppur had a mean cycle time of 61.8 minutes and a standard deviation of 4.8, with a confidence interval of 60.7 to 62.9 minutes.

Karur recorded the shortest mean cycle time at 60.4 minutes, with a standard deviation of 5.1 and a confidence interval of 59.3–61.5 minutes, as illustrated in figure 6. All regions showed statistically significant results ($p < 0.05$). Additionally, the overall sigma level was measured at –3.36 with a standard deviation of 0.2 and a 95% confidence interval of –3.38 to –3.34, indicating a need for significant process improvements to reduce defects and enhance efficiency.

Table 3

ANALYSIS OF MEASURE PHASE (HYPOTHESIS 2)					
Metric	**Region**	**Mean value (Pre)**	**Standard deviation**	**P-value**	**Confidence interval (95%)**
Cycle time	Coimbatore	64.2 minutes	5.2	<0.05	63.1 – 65.3 minutes
	Tiruppur	61.8 minutes	4.8	<0.05	60.7 – 62.9 minutes
	Karur	60.4 minutes	5.1	<0.05	59.3 – 61.5 minutes
Sigma level	Overall	–3.36	0.2	<0.05	–3.38 – –3.34

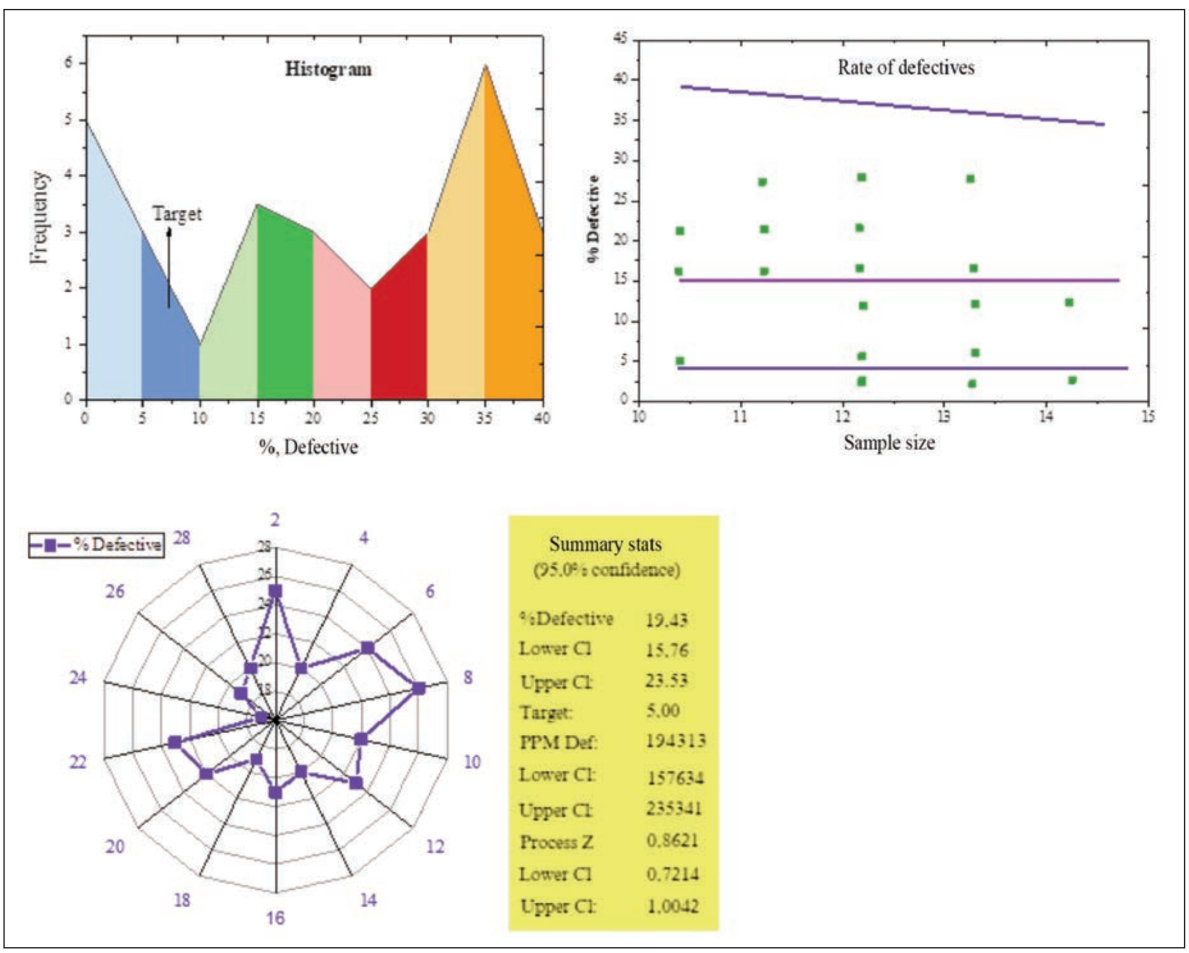

Fig. 6. Binomial process analysis of garment defects

Analyse phase

H_3: Process inefficiencies and raw material variability drive high defect rates.

Table 4 and figure 7 outline the evaluation of the Analyse phase for Hypothesis 3, identifying key root-cause categories, their frequencies, and their impact on defects. Variations in equipment performance, workforce experience, and automation levels led to differences in defect rates and process efficiency across textile companies in this phase. Workflow inefficiencies, including bottlenecks and poor workstation layouts, increased cycle times, while environmental factors like humidity affected fabric quality. Addressing these challenges through optimised scheduling, better maintenance, and controlled environmental conditions can enhance productivity and quality. Machinery issues were the most significant, occurring 120 times and contributing to 35.0% of defects, with a highly significant p-value (<0.01). Workforce errors accounted for 90 occurrences, representing 25.0% of defects, and were statistically significant (p-value < 0.01).

Material inconsistency, with a frequency of 80 and a 20.0% impact on defects, similarly had a significant p-value (<0.01). Workflow inefficiency was identified in 60 cases, accounting for 15.0% of defects, and was statistically significant (p-value < 0.05).

Environmental factors, though less frequent (40 cases) and contributing only 5.0%, were also statistically significant (p-value < 0.05). These findings emphasise the critical need to address machinery issues and workforce errors as primary areas for defect reduction.

Table 4

EVALUATION OF ANALYSE PHASE (HYPOTHESIS 3)

Root cause category	Frequency	Impact on defects (%)	P-value
Machinery issues	120	35.0	<0.01
Workforce errors	90	25.0	<0.01
Material inconsistency	80	20.0	<0.01
Workflow inefficiency	60	15.0	<0.05
Environmental factors	40	5.0	<0.05

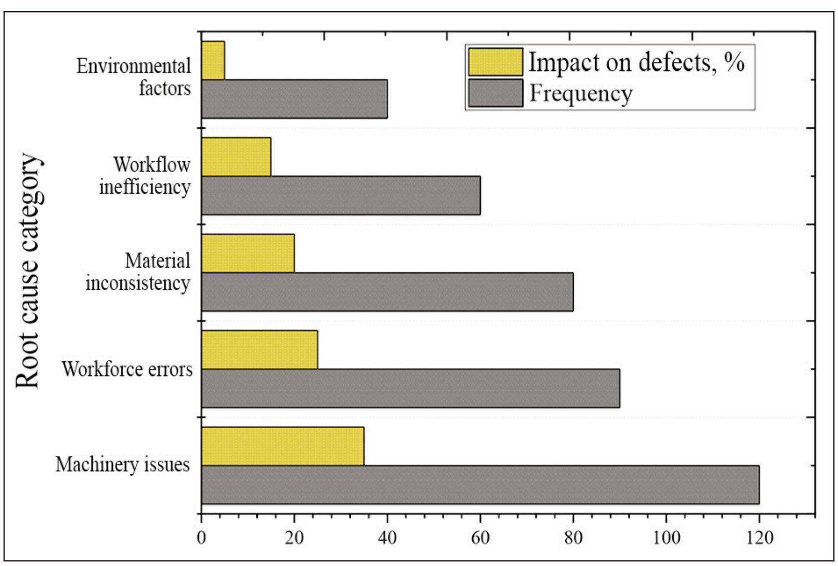

Fig. 7. Hypothesis 3 analysis

Improve phase

H_4: Lean Six Sigma tools will reduce cycle time and improve product quality.

The study applied Lean Six Sigma strategies, including Value Stream Mapping (VSM), preventive maintenance, employee training, Statistical Process Control (SPC), and workstation optimisation, to improve efficiency. Table 5 and figure 8 are based on real-time observations and statistical analysis, showing reductions in cycle time, defect rates, and process variability, validated through hypothesis testing and control charts. Figure 8 compares the initial cycle time (CT) performance with the new process status after improvement, focusing on the mean CT, deviation, and probabilities. The improved process has a mean CT of approximately 55 minutes, with a probability of 0.28 and a standard deviation of 0.1, highlighting its optimised performance. The probability decreases significantly at lower CT values (50 minutes: probability 0.15, deviation 0) and at higher CT values (60 minutes: probability 0.15, deviation 0.2). Extreme CT values, such as 45 and 70 minutes, are absent in the improved process, reflecting a significant reduction in variability. This analysis underscores the success of the improvements in stabilising CT and enhancing overall process efficiency.

The cycle time was reduced from 62.5 minutes to 53.1 minutes, reflecting a 15.0% improvement with a statistically significant p-value (<0.05), as shown in table 5.

The defect rate fell from 19.43% to 12.38%, representing a 36.3% improvement, with a significant p-value (<0.05). Additionally, the sigma level improved dramatically from –3.36 to 0.41, representing a 3.77-unit improvement with high statistical significance (p-value < 0.01). Figure 9 displays the VSM. These results demonstrate the effectiveness of the implemented measures in enhancing operational efficiency and quality control.

Control phase

H_5: Control measures will sustain improvements in efficiency and quality.

Table 6 presents the evaluation of the Control phase for Hypothesis 5, focusing on key metrics to assess stability and consistency after the improvement. The cycle time

Table 5

EVALUATION OF IMPROVED PHASE (HYPOTHESIS 4)				
Metric	**Pre-improvement value**	**Post-improvement value**	**Improvement (%)**	**P-value**
Cycle Time (minutes)	62.5	53.1	15.0	<0.05
Defect Rate (%)	19.43	12.38	36.3	<0.05
Sigma Level	–3.36	0.41	3.77	<0.01

increased slightly from 53.1 minutes to 53.4 minutes, with minimal variance (0.6%) and a statistically insignificant p-value (>0.05). Similarly, the defect rate increased by a negligible 0.3% from 12.38% to 12.42%, which is statistically insignificant (p-value > 0.05). The sigma level declined slightly from 0.41 to 0.40, with a variance of –0.2% and no statistical significance (p-value > 0.05). These findings suggest that the process improvements achieved in earlier phases have been effectively sustained, with only marginal variations in the evaluated metrics.

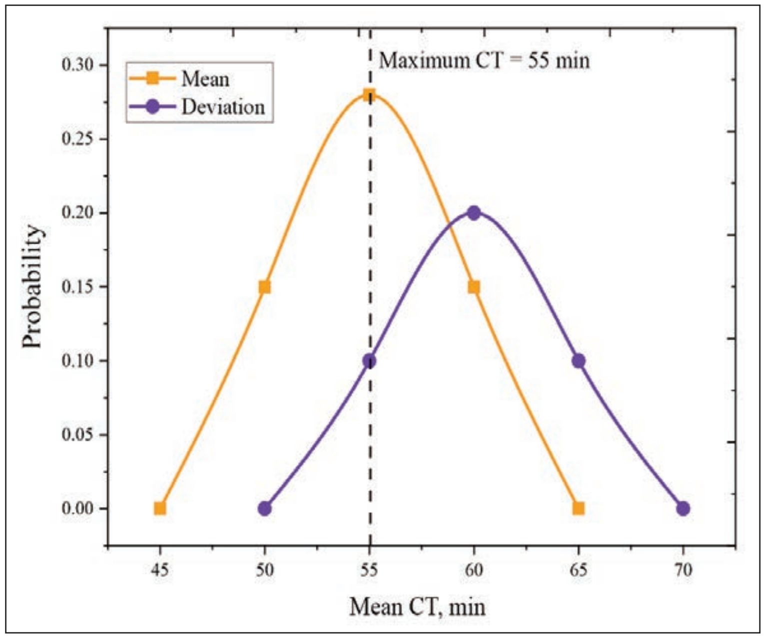

Fig. 8. Initial CT performance compared with the enhanced process

Figure 10 presents the I-MR P control chart used to monitor cycle time (CT) after the finalisation process, detailing both individual values and moving ranges across observations. The individual values show cycle times fluctuating between 50 and 55 minutes, with peaks at observations 7 (55 minutes) and 13 (55 minutes), and the lowest value at observation 11 (50 minutes). The moving range highlights variations in CT, ranging from 0 (observation 3) to a maximum of 4.5 (observation 11), reflecting significant process variability at certain points. Observations like 9 and 13 indicate

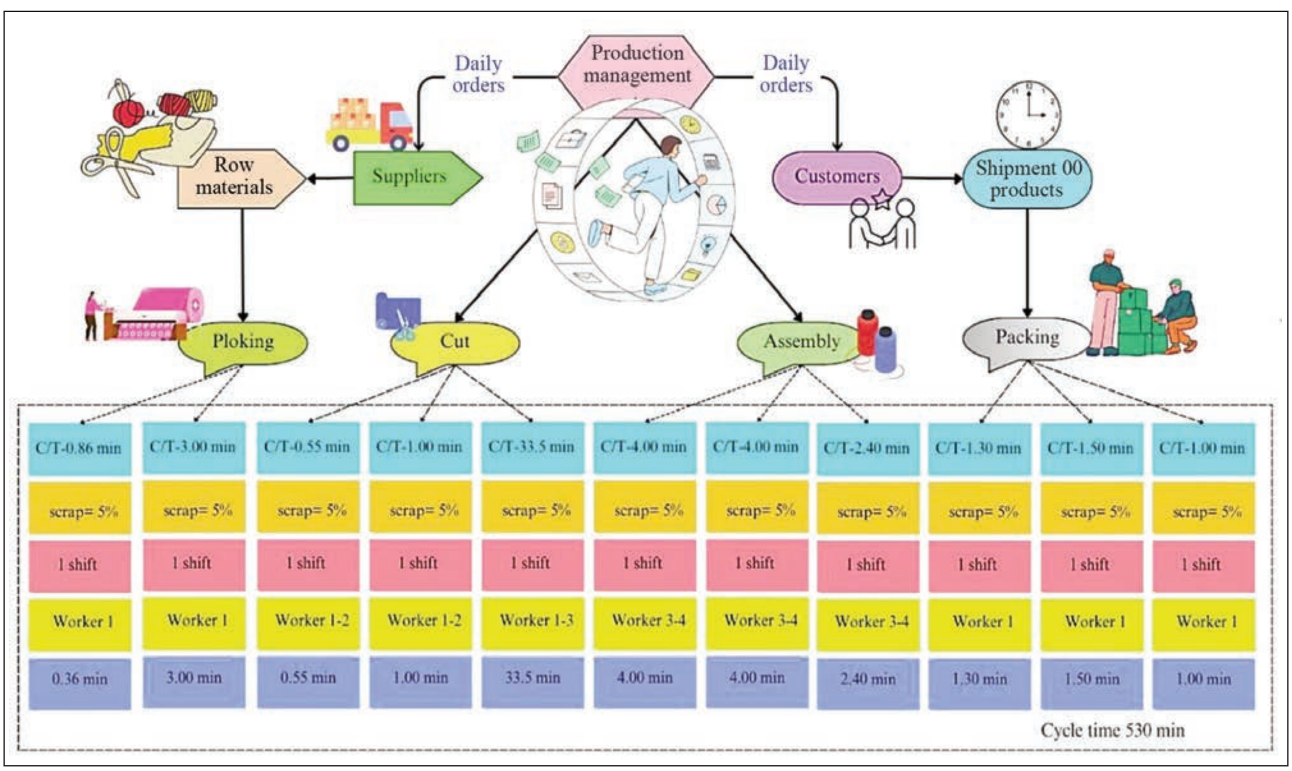

Fig. 9. Value stream mapping enhancements for textile manufacturing

Table 6

EVALUATION OF ANALYSE PHASE (HYPOTHESIS 5)				
Metric	**Baseline value**	**Post-control value**	**Variance (%)**	**P-value**
Cycle time (minutes)	53.1	53.4	0.6	>0.05
Defect rate (%)	12.38	12.42	0.3	>0.05
Sigma level	0.41	0.40	–0.2	>0.05

notable shifts, suggesting potential deviations that may require further analysis. This chart provides valuable insights into process stability and highlights areas for improving consistency in cycle time performance.

Figure 11 illustrates the P control chart used to monitor the proportion of non-conforming (NC) products after the finalisation process. The chart plots the proportion of NC products across 15 samples, highlighting variations in the production process. The proportions range from 0 (samples 4 and 20) to a peak of 0.4 (sample 14). Notable fluctuations include higher proportions in samples 2 (0.25), 10 (0.3), and 18 (0.25), while lower proportions are observed in samples 22 (0.05), 12 (0.12), and 28 (0.12). The data highlights significant variability in the NC product percentage, with some samples meeting acceptable quality standards (near zero) while others exceed typical control limits. This analysis emphasises the need for continuous monitoring and corrective actions to maintain consistent product quality.

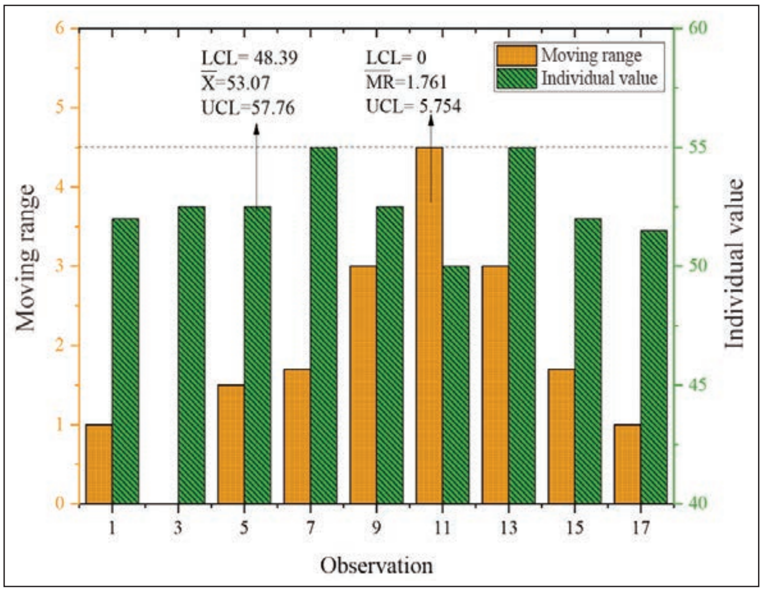

Fig. 10. Monitoring CT performance using the I-MR p chart

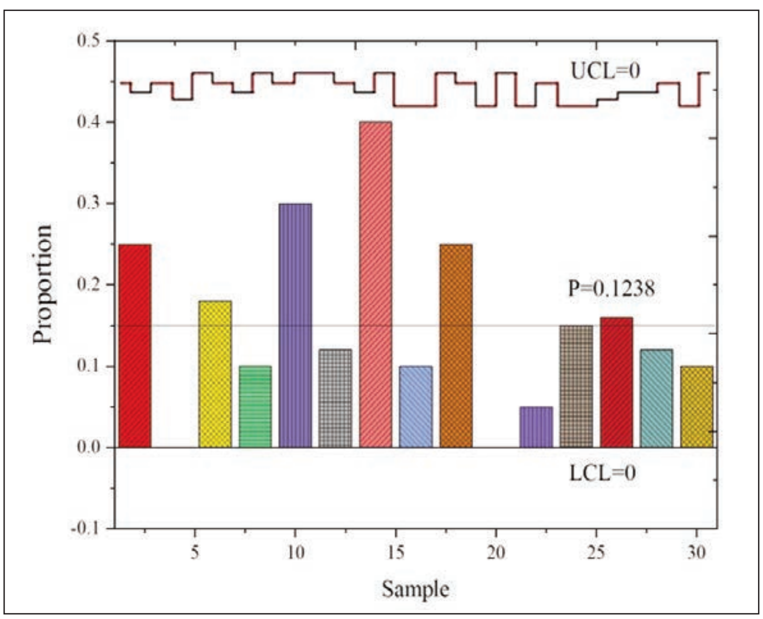

Fig. 11. Monitoring the NC product percentage with a P chart

DISCUSSION

This study outlines the specific improvements achieved through Lean Six Sigma. These include a 15% reduction in cycle time (from 62.5 to 53.1 minutes), a 36.3% decrease in defect rate (from 19.43% to 12.38%), and an improvement in the sigma level from –3.36 to 0.41. The impact of process changes – such as Value Stream Mapping (VSM), Statistical Process Control (SPC), and preventive maintenance – will be explicitly linked to these results to clarify the connection between interventions and outcomes.

CONCLUSION

The implementation of Lean Six Sigma in the Tamil Nadu textile sector has demonstrated significant improvements in both operational efficiency and product quality. The study addressed critical inefficiencies using a structured approach that included the DMAIC framework, resulting in a 15% reduction in cycle times and a 36.3% reduction in defects. Hypothesis testing was used to validate the data-driven improvements, and p-values verified that the changes were statistically significant. These findings demonstrate not only how well Lean Six Sigma streamlines textile production but also how it can raise textile companies' competitiveness.

Manufacturers can increase their market share, lower operating costs, and improve customer satisfaction by optimising production schedules and quality control. The results highlight the importance of incorporating Lean Six Sigma and other quality management systems into the daily operations of textile manufacturing facilities. The post-control phase shows that the gains are long-lasting, as the metrics remain steady and there are few deviations. The gains in cycle time and defect reduction will be maintained through ongoing monitoring and recurring audits, which will also enable the identification and implementation of any necessary additional improvements. Overall, the study shows how Lean Six Sigma can be scaled to address broader operational issues in the manufacturing sector and offers a roadmap for enhancing textile production processes. Businesses that adopt these approaches can build resilience and long-term growth in an increasingly competitive global market.

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Impact of cleaning process modifications on the efficiency of improved working parts

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ABSTRACT – REZUMAT

Impact of cleaning process modifications on the efficiency of improved working parts

In the context of increasing demands for cotton fibre quality and energy-efficient processing, this study focuses on enhancing the effectiveness of cleaning systems by modifying working parts in fibre cleaning machines. The research investigates the influence of guiding devices and the geometric profile of grates on flow behaviour and pressure distribution in dual-drum saw-type fibre cleaners. A mathematical model based on the compressible flow of fibrous material was developed to describe the interaction between the fibre stream and the inclined grate surfaces. The pressure-density relationship and flow velocity were analysed through nonlinear differential equations, and analytical solutions were obtained under specific boundary conditions. Simulation results demonstrate that changes in the initial thickness of the fibre stream and the shape of the guiding device significantly affect the cleaning efficiency. An optimised profile of the guiding system reduces fibre loss and improves impurity removal by up to 15% compared to conventional systems. The proposed modifications offer a promising solution for adapting fibre cleaning equipment to handle machine-harvested, highly contaminated cotton in modern ginning operations.

Keywords: *cotton fibre, fibre cleaner, guiding device, flow modelling, pressure distribution, cleaning efficiency*

Impactul modificărilor procesului de curățare asupra eficienței pieselor de lucru îmbunătățite

În contextul cerințelor tot mai mari privind calitatea fibrelor de bumbac și eficiența energetică a procesării, acest studiu se concentrează pe îmbunătățirea eficienței sistemelor de curățare prin modificarea pieselor de lucru ale mașinilor de curățat fibre. Cercetarea investighează influența dispozitivelor de ghidare și a profilului geometric al grătarelor asupra comportamentului fluxului și distribuției presiunii în cazul curățătorilor de fibre cu doi tamburi de tip ferăstrău. A fost dezvoltat un model matematic bazat pe fluxul compresibil al materialului fibros pentru a descrie interacțiunea dintre fluxul de fibre și suprafețele înclinate ale grătarelor. Relația presiune-densitate și viteza de curgere au fost analizate prin ecuații diferențiale neliniare, iar soluțiile analitice au fost obținute în condiții limită specifice. Rezultatele simulării demonstrează că modificările grosimii inițiale a fluxului de fibre și ale formei dispozitivului de ghidare afectează în mod semnificativ eficiența curățării. Un profil optimizat al sistemului de ghidare reduce pierderea de fibre și îmbunătățește eliminarea impurităților cu până la 15% în comparație cu sistemele convenționale. Modificările propuse oferă o soluție promițătoare pentru adaptarea echipamentelor de curățare a fibrelor pentru a trata bumbacul recoltat mecanic și puternic contaminat în operațiunile moderne de egrenare.

Cuvinte-cheie: *fibră de bumbac, curățitor de fibre, dispozitiv de ghidare, modelare a fluxului, distribuția presiunii, eficiență de curățare*

INTRODUCTION

Cotton is one of the most widely used natural fibres in the global textile industry due to its breathability, softness, and renewability. However, the quality of cotton fibre largely depends on its cleaning and processing stages. Contaminants such as seed coat fragments, leaves, stems, and soil particles significantly impact the performance of downstream operations such as spinning and dyeing, as well as the overall textile product quality. In response to the demand for higher quality and more sustainable production methods, recent research has focused on optimising the cotton cleaning process, especially in machine-harvested cotton, which typically contains higher levels of foreign matter [1, 2].

Traditional fibre cleaning machines rely on mechanical separation using saw cylinders and grates. However, excessive mechanical action often leads to fibre damage and increased short fibre content. Therefore, researchers have explored the design of modern cleaning systems that balance impurity removal and fibre preservation through the use of adaptive guiding devices, optimised grate geometry, and intelligent control [3, 4]. Studies using computational fluid dynamics (CFD) and experimental modelling have demonstrated that the thickness, speed, and pressure of the fibre flow significantly affect the cleaning efficiency [5, 6]. Controlling the uniformity of fibre feeding to the saw cylinders using specially designed guide elements has been shown to reduce frictional stress and increase impurity release [7, 8].

In particular, the implementation of double-drum fibre cleaners and modular cleaning units has been proven to enhance performance for difficult-to-clean cotton varieties. These machines allow more precise control of airflow and mechanical interaction within the cleaner, leading to improved impurity removal while reducing fibre loss [9, 10]. Research emphasises that the placement and curvature of guiding devices can significantly influence fibre flow distribution and thus directly impact the final quality of the cleaned cotton [11, 12].

Moreover, innovations in AI-based monitoring and automation are being integrated into cotton cleaning systems to adapt the process parameters in real time based on fibre type and contamination level [13, 14]. These adaptive systems offer a promising path for achieving consistent quality under varying input conditions while optimising energy consumption. Mathematical modelling, such as nonlinear pressure-density formulations and flow dynamics in inclined grate zones, has provided new insights into fibre interactions within cleaning machines [15, 16].

This research aims to assess the impact of modified guiding devices and structural improvements in 2VPM-type fibre cleaners on cleaning efficiency and fibre preservation. By combining theoretical modelling with practical experiments, the study seeks to offer applicable solutions for modernising cotton ginning processes to meet both quality and sustainability goals.

REVIEW OF FIBRE CLEANING EQUIPMENT AND RELATED RESEARCH

One of the most critical parameters influencing the quality of cotton fibre is the content of residual impurities and defects embedded in the fibre matrix. Fibre imperfections can originate from several sources, such as mechanical stress encountered during harvesting and post-harvest processing, or from external contaminants, including seed coats, stems, and soil particles attached during the cotton-growing season [17]. Among these, the residual organic and mineral matter that adheres to raw cotton in the field constitutes the majority of contamination requiring removal in the ginning process.

At modern cotton gin plants, impurities are separated through a multi-stage cleaning line, which typically includes stone catchers, pre-cleaners for coarse and fine contaminants, and dedicated fibre cleaners positioned toward the final stages [18]. While advanced equipment has improved impurity separation, the challenge of minimising fibre damage while maximising cleaning efficiency remains [19].

Historically, many cotton processors relied on three-drum fibre cleaners (e.g., 3OVP) to achieve adequate cleaning. However, due to high energy consumption, these systems were gradually replaced by more energy-efficient single-drum direct-flow cleaners such as the 1VPU model [10, 20]. Despite their lower energy usage, machines like the 1VPU faced limitations. The single saw cylinder and its accompanying four grates could not adequately remove both fine and coarse contaminants, leading to subpar fibre purity, especially in high-grade cotton varieties [21].

Earlier experimental research by Krygin laid the foundation for analysing the impact of grate positioning on the efficiency of impurity separation, while Tursunov explored how the geometry and spacing of grates affected the trajectory of the fibre as it interacted with the drum surface [22, 23].

In processing medium-staple cotton, multi-drum setups are typically arranged in series to improve throughput and efficiency. International equipment manufacturers, such as Platt-Lummus, have introduced aerodynamic fibre cleaners as supplementary units to enhance cleaning, especially for machine-harvested cotton with higher debris loads [24].

American cotton gins widely implement modular systems with circulatory ducts and adjustable valves to tailor the cleaning sequence according to the contamination level of the incoming raw cotton [25].

In recent years, Uzbekistan has also integrated modern equipment within its cotton ginning plants. For example, a complete cleaning line including pneumatic KPK-3000 systems has been installed at the Zhuma gin facility in Samarkand, incorporating both local and Chinese engineering expertise. These upgrades were selected based on compliance with Uzbekistan's textile industry standards [26].

Pneumatic cleaners operate on the principle of differential inertial force, effectively separating lightweight cotton fibres from heavier contaminants via a sharp 120° air-induced turn within the pipeline, enabling waste to be diverted to a collection chamber [27].

Machine test results for these units have shown average cleaning efficiencies ranging from 10–15%, although lower than the declared 18–20% efficiency in the manufacturer's specifications. It was also observed that cleaning efficiency could be enhanced by modifying the shape of the rib edges within the grate, as smaller radii (e.g., 0.3 mm) increased the frictional engagement between fibre and the grate, improving impurity release [28].

As the Uzbek cotton industry transitions toward machine-harvested raw material, the proportion of highly contaminated cotton is expected to rise. This shift necessitates re-engineering existing cleaning systems to accommodate higher volumes and impurity loads. Current fibre cleaning principles, optimised for hand-harvested cotton, must therefore be revised and adapted to newer realities.

In this regard, a comprehensive structural analysis of fibre cleaning mechanisms and the development of adaptable designs is a crucial area of focus. This study continues along this trajectory by evaluating improved guiding and cleaning components through theoretical modelling and real-world implementation. These developments are expected to provide more robust, energy-efficient, and impurity-resistant fibre cleaning systems suitable for contemporary production requirements.

THEORETICAL ANALYSIS AND MODELING APPROACHES IN COTTON FIBRE CLEANING

Several researchers have proposed theoretical approaches to optimise cotton fibre cleaning by analysing fibre–machine interactions. Ismailov introduced a new design of fibre cleaning equipment based on aeromechanical separation principles with variable pitch drum configurations [29]. His work focused on the impulse behaviour of fibre bundles upon contact with differently shaped surfaces, providing experimental data to calibrate models of shock dynamics. These findings were used to define optimal drum geometries for industrial implementation.

Similarly, Kotov investigated the aerodynamics and compression mechanics within a three-stage direct-flow cleaner [30]. He identified that minimising resistance in the compression zone could lead to higher throughput and less fibre damage. His work included the derivation of airflow and pressure loss equations to optimise the internal geometry of cleaner housings.

Tursunov applied material mechanics principles to model the impact of grate angle, curvature, and housing materials on fibre movement [23, 31]. He demonstrated that replacing conventional housings with those containing plastic additives reduced fibre waste and improved final yarn uniformity. Furthermore, a transcendental equation system was constructed to simulate the influence of transfer forces on yarn quality, enabling predictions of cleaning outcomes under different mechanical setups.

These theoretical investigations collectively provide a scientific foundation for understanding the dynamics of cotton flow, pressure distribution, and frictional forces in fibre cleaning systems. Building upon these models, this study integrates structural and aerodynamic modifications into a dual-drum cleaner to evaluate their practical impact on cleaning efficiency.

THE INFLUENCE OF THE GUIDING DEVICE ON THE EFFICIENCY OF FIBRE CLEANING

In the process of cleaning the fibre, on fibre cleaners, the amount of fibre released into waste occurs mainly in the brush area, which provides strength with the saw cylinder, which accepts the flow of fibre coming out of the saw gin, disk to the saw cylinder, by knocking the fibre into the kneaders installed under the cylinder, due to the low technological process of the saw cylinder. This condition occurs in the area of the first saw cylinder, which receives and cleans the fibre stream coming from the gin of a two-drum direct-flow fibre cleaner brand 2VPM. By increasing the viscosity of the fibre flow to the first cylinder of the saw, it is advisable to install a guide device in the area of the fastening brush to dramatically reduce the separation of fibre waste between the saw cylinder and the fastening brush and increase the amount of fibre produced.

We will conduct theoretical studies on the good adhesion of the moving fibre to the saw teeth of the saw cylinder of the guide device.

Numerous theoretical and practical studies have been conducted on the effect of the impact force applied to the flow of cotton fibre moving in the area of saw cylinders and grates on the cleaning efficiency. However, the process of changing the initial thickness of the cotton fibre using special guiding devices and the pressure exerted by the columns on the fibre flow of a given thickness has not been studied, and the effect of velocity changes on density changes has not been revealed. It is known that the thickness of the fibre stream varies from 4 mm to 15 mm when the fibre coming from the saw gin meets the first saw cylinder. We will make the following assumptions to simulate the effect of this range on the cleaning efficiency of the fibre cleaner.

1. We assume that the fibre mass, the contact medium, and the flow movement are stationary, and in this case, the fibre flow rate in the grate area is constant and equal to Q_0. The impurities released from the stream during the cleaning Q_0. The process does not affect performance.
2. The flow movement between the grates is considered to be one-dimensional.
3. We assume that the surface of the grates affected by the fibre has the shape of an inclined plane. They will be located at the same distance from each other in the cleaning area.
4. An arbitrary colony arrives in contact with a fibre stream, and its interaction is determined by Hertz's law or an experimental method. We denote the velocity, pressure, density (parameters), and cross-sectional area of the flow between each grate by v_i, p_i, and S_i accordingly. Here (i = 1 … n), n – number of columns.

First, we will determine the pressure change indicators between the first and second grades of the fibre cleaner.

Let's imagine that the parameters of the initial (without taking into account the grate area) flow indicators are equal to ρ_0, v_0, h_0, and S_0 (figure 1). Let the thickness of the fibre stream in front of the first grate be equal, in this case, the flow performance is equal to $Q_0 = \rho_0 v_0 h_0 L$, where L *is* drum length.

The flow layer with the first grate is an interaction zone $A_1B_1C_1D_1$, and flow parameters are determined in this zone. Let us place the origin at point 0. The flow layer with the first grate is an interaction zone $A_1B_1C_1D_1$, and flow parameters are determined in this zone. To determine the flow layer between the first grate and the saw drum, we determine the starting and ending points A_1 and C_1 concerning the variable S:

$$b = [h + (h_0 - h)S/S_0]L_k \qquad 0 < x < S_0 \qquad (1)$$

where h_0 is primary fibre thickness; h – the maximum approximate distance of the grate to the ceiling; S_0 – length of the obliquely flat section of the grate; L – drum length; L_k – separation of fibres in contact with the grates, $k = L_1/L < 1$.

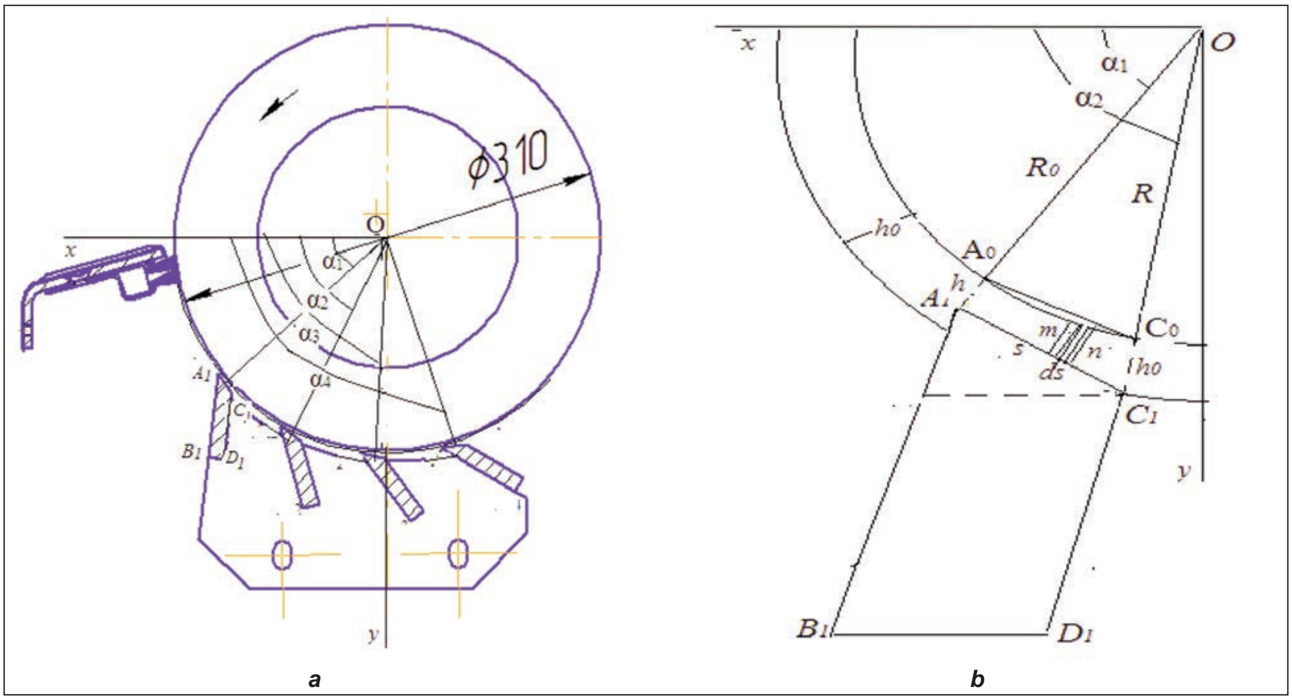

Fig. 1. Graph of the dependence of the flow thickness of the improved fibre cleaner h_0: *a* – the layout of the grates in the cleaning area; *b* – the calculation scheme of the layer thickness at the location of the grates in the saw cylinder

For a separated element *mn* in stationary driving conditions, we formulate the Euler equation:

$$-[Sp + \mathrm{d}(Sp)] + Sp - qL\beta \mathrm{d}x = \rho v S \mathrm{d}v \quad (2)$$

where $q = fp$ – lateral pressure; f_1 and f_2 – relative coefficients of friction between the fibre with the drum and the grates $f = f_1 + f_2$.

Considering the equation $S = b(S)L$ and the expression *q,* divide the expression into d*x*, we obtain the following equation.

$$\rho v b \frac{\mathrm{d}v}{\mathrm{d}s} = -\frac{\mathrm{d}(pb)}{\mathrm{d}s} - kfp \quad \text{here} \quad b = h + \frac{h - h_0}{S_0} S \quad (3)$$

The unknowns ρ, *v*, *b* and *p* are involved in equation 3. To fill it out, we use the third formula.

To solve the problem, first assume and assume that the flow stationarity condition is the following:

$$\rho v b = \rho_0 v_0 b_0 = Q_0/L \quad (4)$$

Secondly, the equation of state of the medium should be appropriate. To do this, let's take the relationship between pressure and density. According to the research work of Sevostyanov A.G., a linear relationship between small pressure values is advisable ($p \le 10^5$ Pa), t.e.

$$\rho = \rho_0[1 + B(p - p_0)] \quad (5)$$

where p_0 is initial fibre pressure, *B* – coefficient obtained as a result of practical experiments.

Using relations 4 and 5, we determine the expression for pressure through velocity.

$$p = p_0 + \frac{1}{B}\left(\frac{v_0 h_0}{vb} - 1\right)$$

$$\left(1 - \frac{c^2}{v^2}\right)\frac{\mathrm{d}v}{\mathrm{d}x} = -\frac{c^2}{v_0 b_0}[b' + fk(p_0 B - 1)] - \frac{c^2 fk}{vb} \quad (6)$$

If we substitute the expression $b' = x/R_0$ into this equation, then the equation will look like this:

$$\frac{\mathrm{d}v}{\mathrm{d}x} = -\frac{c^2}{v_0 b_0 a}\left[\frac{h_0 - h}{R_0} + fk(p_0 B - 1)\right] - \frac{c^2 fk}{vba} \quad (7)$$

here bulk compression modulus of the medium $a = 1 - c^2/v^2$, $c = \sqrt{K/\rho_0}$, $K = 1/B$.

Equation 8 defines the flow velocity in the gap in contact with the grate. The equation is integrated under the following initial condition $S = 0$, $v = v_0 = Q_0/\rho_0 h_0 L$. Since the equation is nonlinear, it is solved in a conical manner. In some cases, the equation can be reduced to a linear form. Let us solve the relationship 7 for the velocity.

$$v = \delta_1 = \frac{v_0}{1 + B(p - p_0)} \quad (8)$$

Because in the cleaning zone $\frac{p}{p_0} < 1$, then in the cleaning zone, there should be $\Delta p < 0$. In the case of small values $B \le 1$ and the difference $\Delta p = p_0 - p$, we extend the expression to the line.

$$v = \delta_2 = v_0[1 - B(p - p_0)] \quad (9)$$

By changing expression 8 to 9, we estimate the relative error $\Delta p = p - p_0$ in percent for different values of the coefficient *B*. We define them by the ratio of the difference δ to δ_1.

$$\delta = \frac{100(\delta_1 - \delta_2)}{\delta_1} = 100 B^2 \Delta p^2 \quad (10)$$

The table shows the maximum values of Δp_m each error $\delta(\%)$ for different values of *B* for a given pressure coefficient $\Delta p = p_0 - p$. If, when solving problem 9, the error $\delta(\%)$ used by the connection is given, then in this case the condition $\Delta p \le \Delta p_m$ for pressure in the calculation process must be satisfied.

Table 1

MAXIMUM PERMISSIBLE PRESSURE Δp_m AT DIFFERENT VALUES OF B AND δ(%)										
	B = 0.0005 Pa^{-1}					**B = 0.001 Pa^{-1}**				
δ(%)	1	3	5	8	10	1	3	5	8	10
Δp_m(Pa)	200	346.2	447.2	565.7	632.4	100	173.2	223.6	282.8	316.2
	B = 0.0015 Pa^{-1}					**B = 0.002 Pa^{-1}**				
δ(%)	1	3	5	8	10	1	3	5	8	10
Δp_m(Pa)	67.7	115.5	149.1	188.6	210.8	50	86.6	111.8	141.4	158.1

For example, if it is known for fibrous material $B = 0.0015$ Pa^{-1}, then the pressure calculated from the results of the table should not exceed $\Delta p = p_0 - p$ 115.5 Pa so that the error in using formula 10 does not exceed 3%. In order not to exceed the error, the pressure should not exceed $\Delta p = p_0 - p$ 210.8 Pa. Using the relationship (9), the equation takes the following form of a linear equation.

$$(M^2 h_0 - b)\frac{dv}{dx} = -(b' + fk)[(p_0 B + 1)v_0 - v] \quad (11)$$

If we put the expression b, then the variables of the equation will be separated

$$\frac{dv}{(p_0 B + 1)v_0 - v} = -\frac{b_0}{a_0 - S}\, ds \quad \text{at } 0 < S < S_0$$

where the speed of propagation of waves in a medium is

$$a_0 = \frac{M^2 h_0 - h}{h_0 - h}, \quad b_0 = \frac{h_0 - h + fkS_0}{h_0 - h}. \qquad M = v_0 / c, \quad c = \sqrt{1/(B\rho_0)} \quad (12)$$

The solution in the condition $v(0) = v_0$ of equation 12 according to the value of M looks like this:

$$M < \sqrt{h/h_0}:$$

$$v = v_0\left\{1 + \frac{p_0}{\rho_0 c^2}\left[1 - \left(\frac{a_1}{a_1 + S}\right)^{b_0}\right]\right\} \quad 0 < S < S_0 \quad (13)$$

$$M = \sqrt{h/h_0}:$$

$$v = v_0\left[1 - \frac{p_0}{\rho_0 c^2}\left(\frac{S}{S_1} - 1\right)\right] \quad S_1 < S < S_0 \quad (14)$$

$$M > \sqrt{h/h_0}:$$

$$v = v_0\left\{\frac{p_0}{\rho_0 c^2}\left[1 - \left(\frac{a_2}{a_2 - S}\right)^{b_0}\right]\right\} \quad S_0 < a_2 \text{ at } 0 < S < S_2 \quad (15)$$

$$v = v_0\left\{1 + \frac{p_0}{\rho_0 c^2}\left[1 - \left(\frac{a_2}{a_2 - S}\right)^{b_0}\right]\right\} \quad 0 < S < S_2, \qquad v = v_1 \quad S_2 < S < S_0 \quad S_0 > a_2 \quad (16)$$

$$\text{here: } a_1 = \frac{(h - M^2 h_0)S_0}{h_0 - h}, \quad a_2 = \frac{(M^2 h_0 - h)S_0}{h_0 - h}$$

$$v_1 = v_0\{1 - Bp_0[(1 - S_2/a_2)^{-b_0} - 1]\} \quad (17)$$

Since equation 12 has singular points when $M > \sqrt{h/h_0}$ at $S = S_0$ and where $M = \sqrt{h/h_0}$ at $S = 0$ (14–17) the distances S_1, S_2 are obtained arbitrarily. From the analysis of formulas 13–16, it can be seen that when the flow rate decreases, its speed decreases, and the density increases according to formula 5: $M \geq \sqrt{h/h_0}$. According to the requirements of the cleaning technology, in order for the cleaning process to be carried out, the flow density must be reduced. This can be observed when $M < \sqrt{h/h_0}$, therefore, for the calculation we will use the above formula 13.

ANALYTICAL MODELING AND NUMERICAL CALCULATIONS

According to the obtained equations, it is necessary to study the influence of the pressure in the grate on the influence of the density speed and the efficiency of the fibre cleaner with an initial raw material thickness from 4 mm to 15 mm. Here ρ_0 = 15 kg/m^3, h = 0.011 m, $f_1 = f_2 = 0.3$, L = 2.4 m, S_0 = 0.02 m.

Figure 2 shows the graphs of the change in flow rate (a) and raw cotton density (b) for two different values of the pressure coefficient B and initial pressure p_0 relative to the variable S in the layer between the grate and the saw cylinder. The calculations are performed for the following values of the parameters: ρ_0 = 15 kg/m, h_0 = 0.014 m, h = 0.011 m, $f_1 = f_2 = 0.3$, β = 0.5, L = 2.4 m, S_0 = 0.02 m, Q_0 = 4000 kg/hour. The error in the selected values of the coefficient B and pressure p_0 did not exceed 12% according to formula 11. From the analysis of the graphs it is evident that an increase in the initial pressure leads to an increase in the flow rate and, consequently, as a result, the fibre becomes thinner. This pattern is also observed with an increase in the coefficient B of fibre rigidity (the inverse of the compression modulus ($K = 1/B$). For example, the salting coefficient is = 0.001 Pa^{-1} ($K = 10^3$ Pa), then the variable is $S = S_0$, that is, after the zone of mutual contact with the first grate, the flow density decreases to 11.8 kg/m^3 if at B = 0.002 Pa^{-1} ($K = 5 \cdot 10^2$ Pa), then this value is equal to 10.4 kg/m^3.

Based on the expression of speed 14–17, the flow density can be determined by formula (4). In this case, based on the model proposed in the work, it is possible to theoretically study the process of cleaning the flow from contaminants.

According to this model, the reduction in cotton mass during cleaning is determined by the following relationship between the flow densities:

$$\frac{dm}{m} = \frac{1}{1+a}\frac{d\rho}{\rho} \quad (18)$$

where $a > 0$ is experimental constant coefficient.

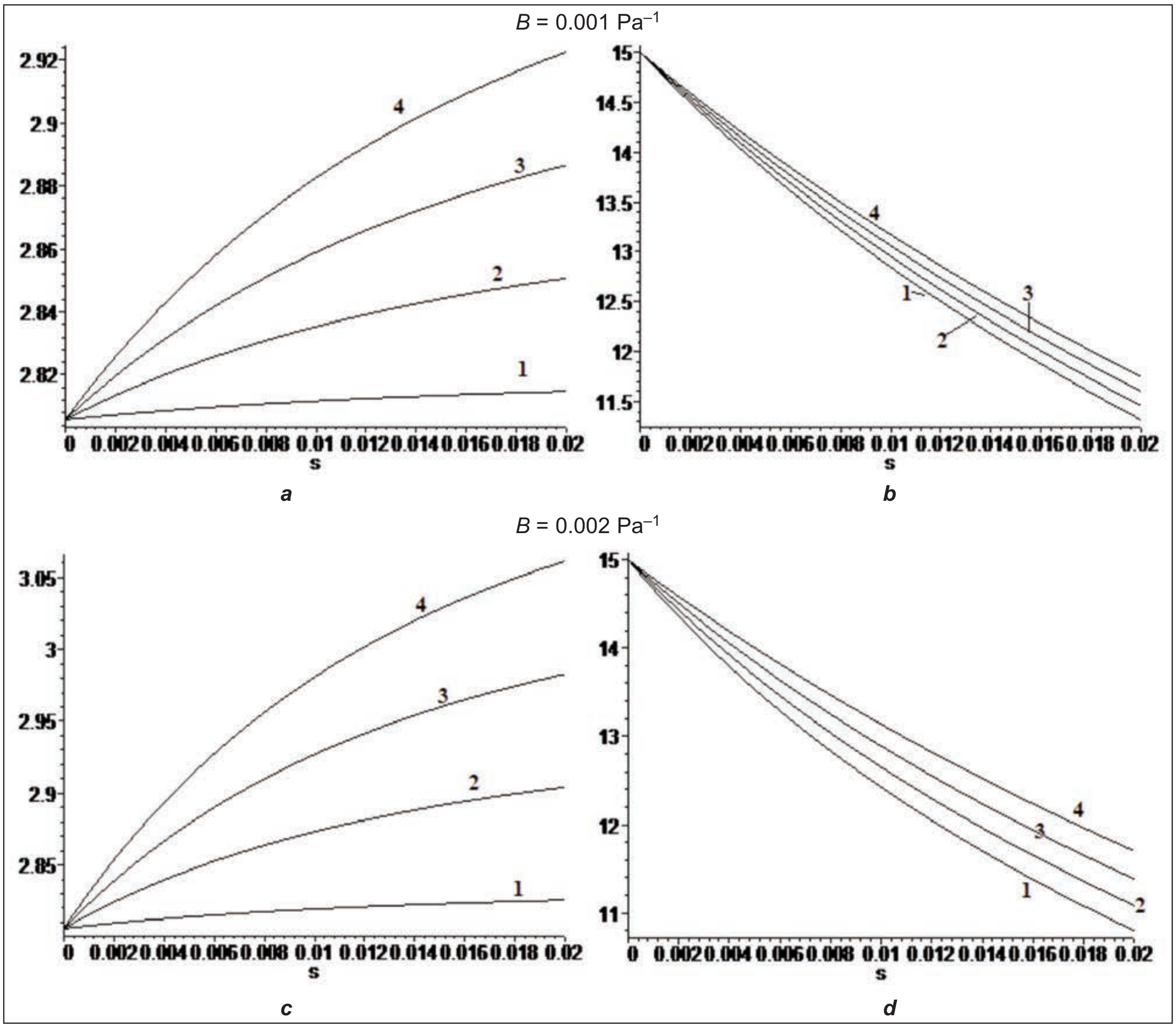

Fig. 2. Distribution graphs in the cleaning zone at different values of the second and initial pressure p_0 (Pa) of the salting coefficient B of raw cotton speed v (m/c) and the cleaning efficiency coefficient ε (%). $1 \rightarrow p_0 = 5$, $2 \rightarrow p_0 = 25$, $3 \rightarrow p_0 = 45$, $4 \rightarrow p_0 = 65$: *a* – flow velocity distribution at $B = 0.001$ Pa^{-1} ; *b* – fibre density distribution at $B = 0.001$ Pa^{-1}; *c* – flow velocity distribution at $B = 0.002$ Pa^{-1}; *d* – fibre density distribution at $B = 0.002$ Pa^{-1}

We integrate equation 18 under the condition $m = m_0$, $\rho = \rho_0$, $S = 0$

$$\frac{m}{m_0} = \left(\frac{\rho}{\rho_0}\right)^{\lambda}$$

Here, m_0 is the mass of the fibre flowing into the zone per unit time. $\lambda = 1/(1 + a)$. This is the ratio:

$$\varepsilon = \frac{m_0 - m}{m_0} = 1 - \left(\frac{\rho}{\rho_0}\right)^{\lambda} \qquad (19)$$

can be taken as the cleaning efficiency coefficient.

Using formula 5, we reduce expression 19 to the following form

$$\varepsilon = \frac{m_0 - m}{m_0} = 1 - \left(\frac{v_0 h}{v b}\right)^{\lambda} \qquad (20)$$

Here, the speed is determined by the formula 14.

Figure 3 shows the distribution graphs in the cleaning zone at different values of the pressure p_0 and the salting coefficient B of the cleaning coefficient.

The plotted data clearly indicate that both the initial pressure p_0 and the salting coefficient B has a direct positive effect on the efficiency coefficient.

Figure 3 shows that the cleaning efficiency coefficient (as a percentage) depends on the device attached to the saw teeth to increase the cleaning efficiency in the cleaning area, which has been proven in theoretical studies, at different values of the solubility coefficient and initial pressure p_0 (Pa) $1 \rightarrow p_0 = 5$, $2 \rightarrow p_0 = 25$, $3 \rightarrow p_0 = 45$, $4 \rightarrow p_0 = 65$, ε(%). It can be seen from the graphs that the cleaning efficiency coefficient also increases with increasing pressure.

Figure 4 shows the appearance of a specially designed guide mounted on equipment when using fibre cleaners operating in an industrial environment and based on scientific research.

Several scientific studies have been conducted on the production of direct-flow fibre cleaners by improving technological parameters. Based on the research, a new scheme for a direct-flow fibre cleaner was

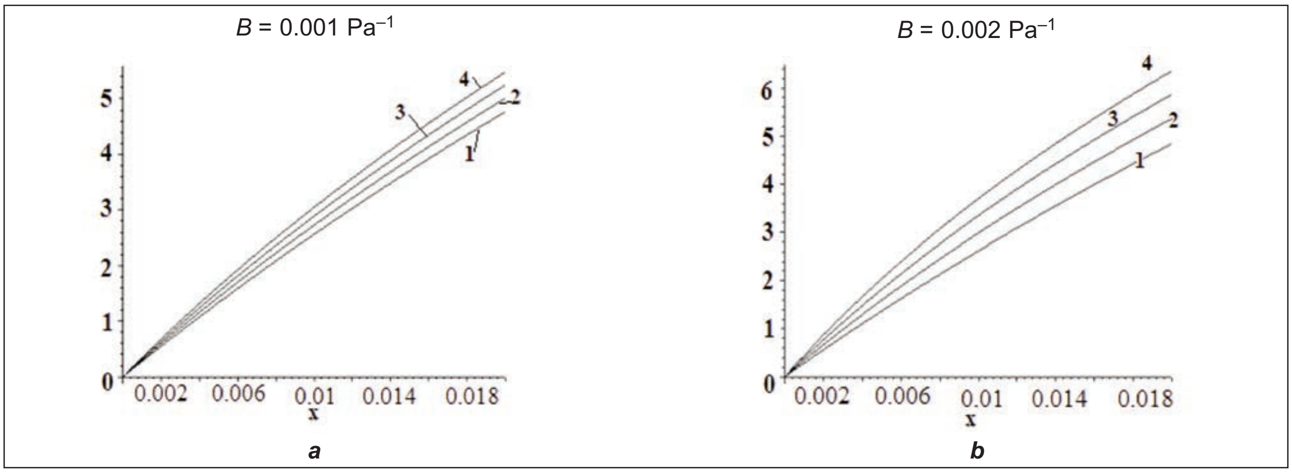

Fig. 3. Cleaning efficiency coefficient ε(%) under different initial pressures p_0 and salting coefficients *B:*
a – distribution at B = 0.001 Pa^{-1}; b – distribution at B = 0.002 Pa^{-1}

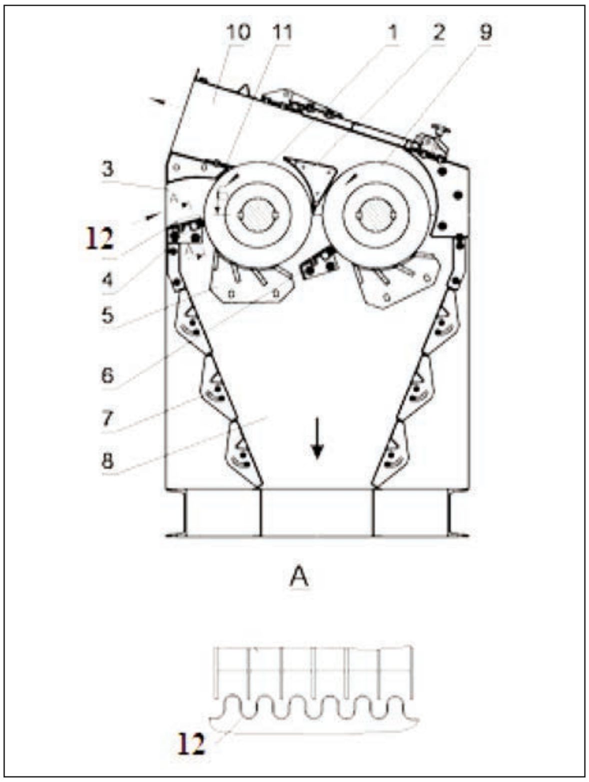

Fig. 4. Fibre cleaner of special design with integrated guiding device: *1* – saw cylinder; *2* – separating knife; *3* – inlet pipe; *4, 6* – attachment brush; *5* – grate; *7* – blinds; *8* – mud hopper; *9* – outlet pipe; *10* – upper housing; *11* – garbage chamber; *12* – specially designed guide

selected, and a specially designed guide was proposed, with which the drawings were made. We can see the proposed guide in figure 5.

To preserve the natural quality of machine-harvested cotton, Uzpakhtasanoat JSC, in particular, Zarbdor Pakhta Tozalash JSC, has introduced resource-saving fibre cleaning equipment [32–33].

Table 2

COMPARATIVE ANALYSIS OF FIBRE CLEANING EQUIPMENT

Naming of indicators	Existing fibre cleaner	Improvements to the advanced fibre cleaner
Fibre performance	2000	2000
Cleaning efficiency (%) – in first grades – in low grades	 30–32 33–35	 35–40 45–49
The number of fibres in the waste intended for spinning	25	20
Electricity consumed	5.5	5.5
Metal consumption	2518	2470

CONCLUSION

This study developed a theoretical model to evaluate the effect of structural improvements, particularly a guiding device, on the performance of dual-drum saw-type

Fig. 5. The proposed guide for a special design

cotton fibre cleaners. The analytical results show that modifying the initial thickness of the fibre stream from 4 mm to 15 mm using the guiding system allows controlling pressure and density distributions across the grate zone. For example, when the salting coefficient is set to B = 0.001 Pa^{-1} with an initial pressure of $K = 10^3$ Pa, the cleaning efficiency increases significantly. A similar trend is observed for B = 0.002 Pa^{-1} at $K = 5 \cdot 10^2$ Pa, where the effective flow pressure reaches 10.4 kPa/m^3, enhancing impurity removal.

From the graphs and simulations, it is confirmed that increasing the initial fibre pressure and flow regulation coefficient B leads to a higher cleaning efficiency. The design of aeromechanical fibre cleaners must therefore include optimised guiding devices that align fibres more accurately with the saw teeth, reducing fibre loss and improving yield.

Based on the theoretical and experimental insights, it is recommended that the proposed guiding device be widely implemented in cotton processing plants, especially for machine-harvested cotton with high impurity content. The findings provide a validated modelling approach and a practical engineering solution for enhancing the performance of modern fibre cleaning systems.

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Modelling of factors of corporate sustainability of textile industry companies

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ABSTRACT – REZUMAT

Modelling of factors of corporate sustainability of textile industry companies

Corporate sustainability significantly affects the commitment of employees in the textile industry, thus providing a basis for recommendations to companies that wish to implement sustainable practices. Factors such as sustainable development practices, job satisfaction, motivation, corporate image, leadership and professional development are key to achieve organizational commitment. The research emphasises the importance of a holistic approach to integrating sustainability into the operations of the textile industry, with a special focus on the environment and responsible business. The research results provide a holistic overview of employee attitudes, highlighting key factors for the successful implementation of sustainability.

Keywords: *sustainable development, textile manufacturing, organisational commitment, employee attitudes, holistic approach*

Modelarea factorilor de sustenabilitate corporativă a companiilor din industria textilă

Sustenabilitatea corporativă afectează în mod semnificativ angajamentul personalului din industria textilă, oferind astfel o bază pentru recomandări companiilor care doresc să implementeze practici durabile. Factori precum practicile de dezvoltare durabilă, satisfacția la locul de muncă, motivația, imaginea corporativă, leadershipul și dezvoltarea profesională sunt esențiali pentru a obține angajamentul organizațional. Cercetarea subliniază importanța unei abordări holistice pentru integrarea sustenabilității în industria textilă, cu un accent special pe mediu și afaceri responsabile. Rezultatele cercetării oferă o imagine de ansamblu holistică asupra atitudinilor angajaților, evidențiind factorii-cheie pentru implementarea cu succes a sustenabilității.

Cuvinte-cheie: *dezvoltare durabilă, producție textilă, angajament organizațional, atitudinea angajaților, abordare holistică*

INTRODUCTION

Modern business, especially in the textile industry, is increasingly demanding sustainable practices that not only contribute to environmental protection but also affect the organisational commitment of employees. This research paper aims to investigate the complex relationship between the application of sustainable development practices in textile companies and the level of commitment of employees. The identification of limitations in previous research lays the foundation for the necessity of additional empirical evidence and for deepening the understanding of this area. The focus of the study is on four key research issues that will be systematically analysed. The first issue investigates specifically how the practice of sustainable development affects the commitment of employees in the textile sector. The second issue seeks to identify specific sustainable development practices that are most effective in fostering employee commitment. The third issue deals with challenges and opportunities in the application of sustainable development practices with the aim of improving the commitment of employees. Finally, the fourth issue analyses best practices that promote sustainability and increase employee commitment within the organisation. Through this study, we aim to obtain empirical evidence that will serve as a basis for recommendations to companies in the implementation of sustainable practices, leading to the improvement of overall business performance. This paper seeks to contribute to the scholarly and practical understanding of the nexus between sustainability and employee commitment, offering evidence-based recommendations to inform future strategic developments within the textile industry.

CORPORATE SUSTAINABILITY IN THE TEXTILE INDUSTRY – OVERVIEW OF PREVIOUS RESEARCH

Previous research examining the modelling of factors influencing corporate sustainability in the textile industry has yielded valuable insights into the complexity and significance of sustainability within this sector. The key elements of previous research highlight the need for a holistic approach that integrates sustainability into all aspects of business [1].

Recently conducted studies have highlighted the significant impact of the textile industry on the environment and society [2], particularly in relation to resource consumption [3] and working conditions in the supply chain [4]. Understanding these impacts becomes crucial for the formation of sustainable practices [5]. The textile industry has a serious negative impact on the environment [6]. Lack of social responsibility in the supply chain [7] further burdens the industry [8], creating poor working conditions and a lack of worker safety [9]. Key steps towards solving these problems include the transition to a circular economy, more efficient use of resources and more responsible business practices to reduce the negative environmental impacts of the textile industry [10]. Environmental practices, social practices within the workplace, and social engagement within the broader community constitute fundamental segments of corporate sustainability. [11]. A focus on reducing negative impact and contributing to the community [12] is becoming essential for sustainable business [13]. These findings underscore the complexity of the factors influencing corporate sustainability within the textile industry and highlight the broader significance of investigating these elements for the advancement of sustainable business practices in this sector.

CONCEPTUAL MODEL OF FACTORS OF CORPORATE SUSTAINABILITY IN THE TEXTILE INDUSTRY

The primary objective of this study is to investigate the influence of sustainable development practices on employee organisational commitment within the context of the textile industry. Initial hypotheses were formulated to identify specific relationships between the manifest variables, and a factor model of corporate sustainability was developed to better understand the interrelationships. The first hypothesis (H1) assumes that *the practice of sustainable development in companies has a positive effect on the organisational commitment of employees*. The second hypothesis (H2) extends the analysis, suggesting that *job satisfaction, motivation and corporate image mediate the positive relationship between sustainable development practices and employees' organisational commitment*. In addition, the third hypothesis (H3) states that *a positive effect of leadership exists on the relationship between sustainable development practices and organisational commitment of employees*.

Following these hypotheses, a model of corporate sustainability factors was developed that could enable a detailed analysis of the relationship between sustainable development practices, job satisfaction, motivation, corporate image, leadership and organisational commitment. This model analyses the influence of job satisfaction, motivation and corporate image on the improvement of employees' organisational commitment. The implementation of sustainable development practices plays a pivotal role in positively influencing these variables, fostering higher levels of organisational commitment, and, in line with the proposed hypotheses, reinforcing the corporate sustainability of textile companies.

In this research on corporate sustainability in the textile industry, a conceptual model was developed that analyses how job satisfaction, motivation and corporate image influence the improvement of employee commitment within the organisation. The goal was to assess how the practice of sustainable development affects these variables and the ultimate corporate sustainability of the company. The conceptual model presented in figure 1 comprises three manifest variables: job satisfaction, employee motivation, and corporate image. These variables are connected to latent variables through three models of factor analysis.

The application of the corporate sustainability factor model in, for instance, the textile industry covers various useful areas. First, companies can use the model to assess their current sustainability performance, including environmental impact, social responsibility and economic viability. This step

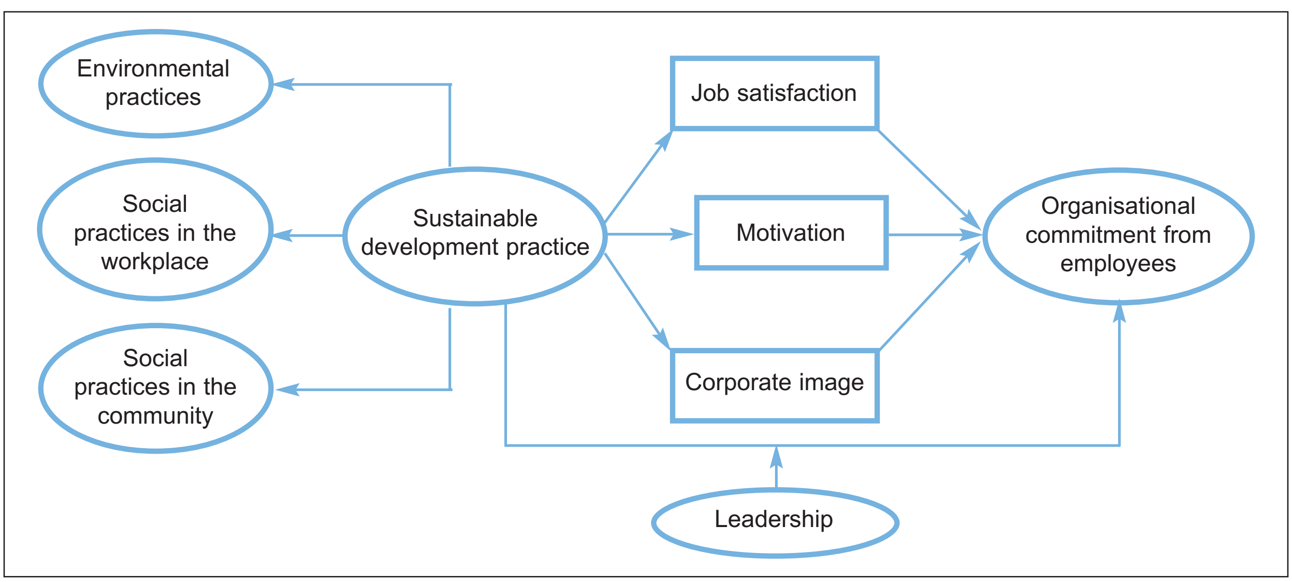

Fig. 1. Conceptual model of corporate sustainability factors in the textile industry

includes setting sustainability goals, sustainability audit, assessment against industry standards and stakeholder engagement. Second, the model can be used for benchmarking against industry standards, allowing companies to identify gaps and set targets for improving sustainability performance [14]. Third, effective communication with stakeholders is key, so companies can use the model to develop transparent sustainability reports, tailored to the needs of key stakeholders. Fourth, the model can serve as a tool for integrating sustainability into business strategy. These include setting specific goals, assessing significance, integrating sustainability into decision-making processes, engaging stakeholders, incorporating sustainability into performance metrics, and investing in innovation. Finally, the model helps identify opportunities for innovation, such as developing products with more sustainable materials or improving energy efficiency. By linking these steps, textile companies can adopt a holistic approach to sustainability, improve their performance and achieve long-term success [15].

In applying the corporate sustainability factor model within the textile industry, it is essential to account for a range of interconnected factors to ensure a comprehensive and holistic approach to sustainability. First, environmental practices are essential, given the significant impact of the textile industry on the environment. This includes the use of sustainable materials, such as organic cotton and recycled polyesters, and the implementation of closed production systems to recycle materials and minimise waste. Second, social practices in the workplace are key to corporate sustainability. This includes ensuring fair working conditions, prohibition of discrimination and forced labour, support for health and safety at work, and support for labour rights, trade unions and labour organisations. Job satisfaction and employee motivation are key to maintaining high performance and long-term sustainability of companies in the textile industry. The fourth factor, corporate image, plays a key role in attracting and retaining customers, investors and the support of the general public.

The aim is to enable textile companies to operate in a sustainable manner, taking into account environmental impacts, social responsibility and economic viability. The first area of application relates to the assessment of current sustainability performance. Companies should set sustainability goals, conduct an audit, assess performance against standards, engage stakeholders, identify areas for improvement, develop an action plan and regularly report on progress. The second area of application is benchmarking against industry standards. This involves identifying relevant standards, collecting data, comparing performance with benchmarks, identifying gaps, developing an action plan and monitoring progress. The third area is communication with stakeholders. Companies should identify key stakeholders, develop sustainability reports, use recognised frameworks, involve stakeholders in the communication process, use different channels and highlight achievements while being transparent about challenges. The fourth area includes the integration of sustainability into business strategy [16]. This entails setting sustainability goals, conducting materiality assessments, integrating sustainability into decision-making processes, engaging stakeholders, incorporating sustainability into performance metrics, investing in innovation and monitoring performance.

The final area pertains to the identification of opportunities for innovation, wherein companies are encouraged to explore sustainable materials, enhance energy efficiency, implement water conservation technologies, minimise the use of hazardous chemicals, adopt circular economy principles, drive supply chain innovation, and integrate digital technologies. These areas of application allow textile companies to successfully direct their efforts towards sustainable business, with the corporate sustainability factor model serving as a guide for achieving and maintaining sustainability in the industry [17].

Factors to consider in the application of the corporate sustainability model in the textile industry include key elements that contribute to achieving sustainable development in this industry. Environmental practices play a key role considering the significant impact of textile production on the environment, and therefore the successful implementation of the model requires the adoption of sustainable materials, efficient management of resources and reduction of the carbon footprint. Social practices in the workplace are essential because they focus on creating fair and safe working conditions. Treating workers with respect, ensuring fair wages and supporting career development are key elements of social sustainability in the textile industry. Social practices in the community contribute to the sustainability of the textile industry, especially in developing countries [18]. This implies respect for international work standards, support for local communities, reduction of the carbon footprint and solving environmental challenges [19]. Job satisfaction and employee motivation have a key impact on the corporate sustainability of the textile industry, as they positively affect productivity, innovation and employee commitment. Corporate image, as a final factor, has a key influence on the success of textile companies. Sustainable practices, support of social goals and business transparency contribute to a positive corporate image. Furthermore, effective leadership plays a key role in achieving corporate sustainability in the textile industry.

METHOD OF THE RESEARCH

The employed methodology offers a comprehensive analysis of corporate sustainability within the textile industry, incorporating both a literature review and conceptual analysis. Initially, it synthesises existing research findings, addressing key themes such as environmental impact, social responsibility, organisational commitment, and leadership. Subsequently, a conceptual model is developed to outline the factors that influence corporate sustainability in this sector.

Through proposing hypotheses and elucidating relationships between variables like sustainable development practices, job satisfaction, motivation, corporate image, leadership, and organisational commitment, it offers a theoretical framework grounded in existing literature and theoretical perspectives. Lastly, the text explores practical applications of this model within the textile industry, delineating strategies for assessing sustainability performance.

The study employed a multifaceted methodological approach, encompassing survey research, statistical analysis, structural equation modelling (SEM), Analytical Hierarchy Process (AHP), and factor analysis. Data from 1236 respondents in Serbia were gathered through a comprehensive questionnaire covering socio-demographic information and 44 statements pertaining to job satisfaction, motivation, corporate image, work experience, personal characteristics, and employee investments. Descriptive statistics were utilised to analyse the demographic composition of the sample, while SEM was applied using Smart PLS 3.0 software to explore intricate relationships between variables like job satisfaction, motivation, corporate image, leadership, environmental practices, social practices, and organisational commitment. Furthermore, the Analytical Hierarchy Process facilitated systematic comparison and evaluation of key criteria and sub-criteria related to sustainable development practices, job satisfaction, motivation, corporate image, and organisational commitment. Additionally, factor analysis was employed to investigate correlations and reliability among the survey items. This methodological blend provided a comprehensive understanding of the factors influencing organisational commitment and sustainability in the textile industry, offering actionable insights for decision-making and strategic planning.

In the first phase, the sustainable development practices of the organisations where the individuals who participated in the research worked were investigated. The SPSS 20 software package was used to process the data collected during the first phase of the research, in combination with the analysis of descriptive statistics of the general sample data. To test for reliability, the Cronbach alpha reliability coefficient was employed. A factor analysis was used to determine the organisational commitment dimensional structures. Cluster analysis was employed to identify the characteristic groups of organisations that exhibit varying degrees of sustainable development practices. The determination of differences that exist between individual groups was carried out using ANOVA and Crosstabs tests. The Expert Choice software package was used to perform calculations using AHP. Expert assessments of the generated characteristics of the groups of organisations that were recognised were used as the basis for this calculation.

The second phase of the research included an analysis of the impact that the sustainable development practices of the organisations included in the research sample have on the organisational commitment of the people employed in them. The basis for this stage was a data set consisting of the responses of the employees who participated in the research. In order to collect information from the employees, a survey was used as a research instrument.

RESULTS AND DISCUSSION

The results in this study were obtained using a sample of 1236 respondents (Serbia) in the period from June 1, 2022, to November 1, 2023. The first stage dealt with the practice of sustainable development of organisations, identifying groups according to employee commitment, and determining the level of commitment. The data was collected using a questionnaire with socio-demographic information and 44 statements about job satisfaction, motivation, corporate image, work experience, personal characteristics and investments of the employee. The respondents were professional staff of organisations, and the research was conducted in order to understand the structure of organisations and the level of organisational commitment of employees. Analysis of descriptive statistics on a sample of 1236 respondents reveals a significant dominance of the female gender (83.3%) compared to the male gender (16.7%). As for age groups, 35% of respondents are aged 18–34, 56.4% are aged 35–54, and 8.7% are older than 55. In relation to education, 46.9% have completed secondary school, while 9.4% have a college degree, and 4.4% have a university degree. Length of work experience shows that 51% of respondents have work experience of 11–21 years, while 93.7% occupy the position of employee. The structural equation modelling (SEM) was used in the data analysis, including factors such as job satisfaction, motivation, corporate image and latent variables for leadership, environmental practices, social practices in the workplace and in the community. The structural equation modelling (SEM) input diagram, presented in figure 1, illustrates the theoretical model under investigation. This diagram includes latent variables, manifest variables, their interrelationships, and the hypothesised causal pathways among them. Fundamentally, the SEM input diagram specifies the hypothesised relationships by indicating how manifest variables are expected to measure latent constructs and how those latent constructs interact with one another.

By means of this diagram, the study's theoretical framework was established, clearly defining the anticipated relationships among variables. Figure 2, titled 'Input Diagram', provides a visual representation of the model's structure and outlines the expected interactions, thereby serving as the foundation for hypothesis testing and model validation.

Conversely, the SEM output diagram, shown in figure 3 and labelled 'Output Diagram,' presents the empirical results derived from the statistical analysis of the theoretical model. This output includes the path coefficients, which reflect the strength and direction of the

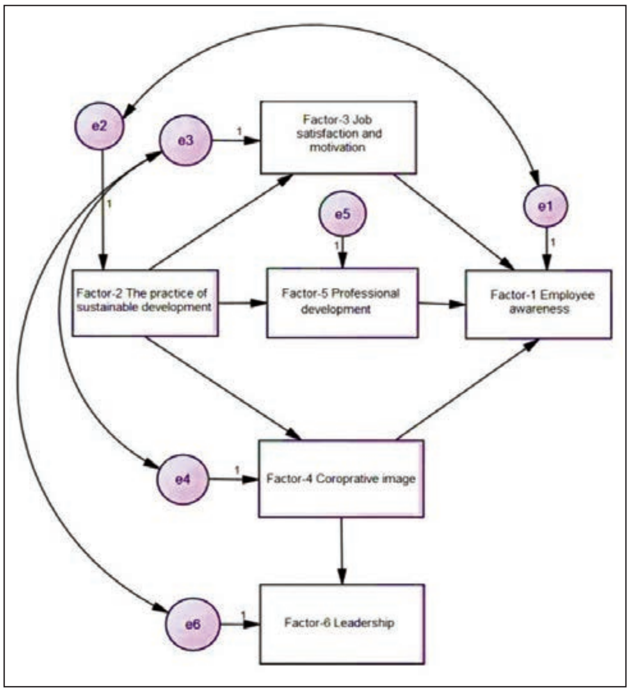

Fig. 2. Input diagram

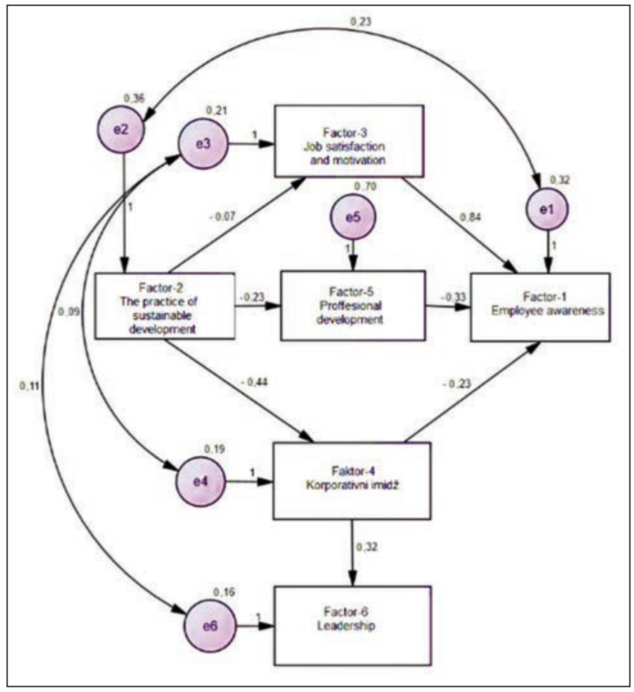

Fig. 3. Output diagram

relationships between latent and manifest variables, offering critical insight into the model's explanatory power and overall validity.

The second phase of the research involved the use of SPSS 20 for data analysis and Expert Choice for applying the Analytical Hierarchy Process (AHP) method. AHP was applied to systematically compare and evaluate key criteria and sub-criteria, including sustainable development practices, job satisfaction, motivation, corporate image and organisational commitment of employees. The procedure included defining criteria, pairwise comparison of their importance, formation of weighting factors, checking the consistency of experts' ratings and final analysis for ranking and prioritisation. AHP enabled the quantification of subjective judgments and provided a structure for informed decision-making in the research areas. This phase aimed to evaluate the impact of sustainable development practices on the organisational commitment of employees.

Through their answers, the respondents expressed their attitudes on various aspects that influence the organisational commitment of employees. Evaluation of factors such as personal characteristics, work experience, employee investment, workplace social practices, professional development and leadership provided a holistic insight into the key determinants of employee commitment in the context of the textile industry.

The majority of respondents believe that personal characteristics and work experience have an insignificant impact on employee commitment, while employee investments are not rated as crucial. Social practices at the workplace, including employee support, according to the majority of respondents, did not show a significant impact. A better workplace environment is rated as an opportunity for professional development, but has less impact on wages and the promotion of diversity.

The most significant factors that contribute to organisational commitment, according to research results, are engagement, greater employee motivation and a proactive approach. Job dissatisfaction did not show a significant impact on innovation. These findings point to the complexity of factors that shape organisational commitment, with an emphasis on motivation, engagement and proactivity as key drivers of increased productivity and enterprise development.

The conducted survey also identified employees' attitudes on the key factors shaping organisational commitment in the textile sector. Corporate image, sustainable development practices, professional development and leadership are recognised as key aspects influencing organisational commitment. These results provide guidelines for the development of strategies aimed at improving the working environment and supporting employees in order to increase employee commitment in the textile industry.

By applying the AHP method, a hierarchy of priorities for the sustainability of the company was established based on five criteria: environmental practices, social practices at the workplace, social practices in the community, corporate image and organisational commitment of employees. In doing so, a methodology for comparing different criteria and alternatives was used in the context of sustainable development practices, job satisfaction, motivation, corporate image and organisational commitment of employees. After the process of comparison and evaluation, weighting factors were obtained for each criterion and subcriterion. Each criterion or sub-criterion has its own weighting factor, a score in relation to the others and a final score that reflects relative importance. These weighting factors reflect the relative importance of

Table 1

WEIGHTING FACTORS											
Summary	**#1 The practice of sustainable development**		**#2 Job satisfaction**		**#3 Motivation**		**#4 Corporate image**		**#5 Organisational commitment of employees**		**Final score**
	Weighting	**Score**	**Weighting**	**Score**	**Weighting**	**Score**	**Weighting**	**Score**	**Weighting**	**Score**	
#A Ecological practice	0.457	0.288	0.196	0.294	0.160	0.484	0.117	0.505	0.070	0.408	0.354
#B Social practice in the workplace	0.457	0.089	0.196	0.160	0.160	0.291	0.117	0.272	0.070	0.274	0.170
#C Social practice in the community	0.457	0.174	0.196	0.080	0.160	0.151	0.117	0.165	0.070	0.208	0.153
#a Leadership	0.457	0.449	0.196	0.466	0.160	0.074	0.117	0.057	0.070	0.110	0.323

each element relative to the others, giving the organisation guidelines for prioritising efforts.

Based on the weighting factors shown in table 1, the practice of sustainable development is considered the most important criterion with a weighting factor of 0.457. Other criteria are ranked according to their importance in relation to this factor. For example, job satisfaction has a weighting factor of 0.196 in relation to sustainable development practices, while motivation has a weighting factor of 0.160.

The results are used to guide the organisation's priorities and make decisions about the focus of improvement efforts. Based on the results, it was concluded that "sustainable development practice" is the most important criterion, with special emphasis on "environmental practice". "Organisational commitment of employees" was rated as the least important. It is recommended that the company focus its efforts on improving environmental practices, social practices in the workplace, and social practices in the community, with an emphasis on leadership as an important subset. The application of AHP methods highlights environmental protection practices and leadership as key factors for achieving company sustainability. Job satisfaction was rated as significant, but not dominant, among sustainability criteria.

A factor analysis was performed to investigate the relationship between the 60 items presented in the correlation matrix. High correlations (>0.60) indicate the possibility of a common factor, while medium correlations (0.20–0.60) indicate a potential association. Assumptions were analysed, including the value of the determinant (>0.00001) and KMO and Bartlett tests were performed. The obtained KMO value (0.773) indicates a high degree of data covariance, and Bartlett's test is statistically significant ($p<0.001$), which confirms the suitability of the data for factor analysis. The principal components method (PCA) was used for factor extraction, which resulted in 6 factors with varimax rotation. Although 7 factors were originally obtained, it was chosen to retain 6 factors in accordance with Catello's scenario and satisfied Cronbach's alpha conditions. Analysis of variance showed a total explained variance of 91.18%. The matrix of rotated factors shows the loadings of the items on the selected factors, which indicates the formation of six clearly defined scales (factors). The reliability of the measurement scales was tested with Cronbach's Alpha coefficients, and the results indicate a satisfactory level of reliability for all factors, with coefficients ranging from 0.959 to 0.999. Analysis of the influence of individual statements on the Cronbach Alpha coefficient did not show the need to eliminate questions in order to maximise the reliability of the measurement scales. Overall, the results support the application of factor analysis to the research data set.

Based on the results of the factor analysis, six factors were identified that relate to different aspects of organisational commitment of employees. Each of these factors comprises a group of questions that together form a specific dimension or concept within the general theme of organisational commitment. Results indicate a high correlation between motivation and commitment of employees towards the organisation. Employees are truly motivated and committed to achieving the organisation's goals. Workplace and sustainability-related questions highlight the connection between workplace characteristics, sustainability and the level of commitment of employees. A quality work environment and sustainable practices contribute to increased commitment. Questions related to identification and initiation emphasise the importance of this dimension in organisational commitment. The feeling of belonging and initiation contribute to a deeper engagement of employees. Corporate image and productivity include questions that investigate the impact of corporate image on employee productivity, as well as employees' emotional connection to work. A clear corporate image has a positive impact on employee commitment and, indirectly, on increasing productivity. Issues related to social practices at the workplace, their impact on the organisational commitment of employees and sustainability are grouped into this factor. The organisation's socially responsible practices contribute to increasing employee commitment, creating a positive impact on the work atmosphere. Leadership and sustainability include issues that explore the role of leadership, the understanding of tensions and conflicts as potential for creative sustainability solutions, and the influence of leadership on the formation of a conceptual model. Leadership plays a key role in shaping the organisational commitment of employees and contributes to sustainable business. Together, these factors constitute the key dimensions of organisational commitment of employees in the analysed context. Their correct interpretation allows a better understanding of the mutual influences of different aspects of organisational commitment.

The research results have great practical applicability and can be used in all organisations operating in the textile industry. Organisations that apply sustainable development practices to a greater extent can use the research results as a basis for implementing various improvements, which can further increase the organisational commitment of their employees. The application of the research results in organisations that do not apply sustainable development practices to an adequate extent in their work can ensure greater use of these practices and the achievement of positive effects associated with them. In this way, in addition to increasing the organisational commitment of employees, numerous other positive effects are achieved for organisations, such as strengthening their public image and increasing the efficiency and quality of operations.

CONCLUSION

This paper investigates the impact of the implementation of corporate sustainability on the commitment of employees in the textile industry, making several key scientific contributions. First of all, this perspective contributes to the development of knowledge about sustainable development within organisational culture. Also, the research represents a step forward in the analysis of the indirect impact of sustainable development practices on the organisational commitment of employees, filling a gap in the literature. The results will enable the development of a model for identifying the impact of corporate sustainability on employee commitment at different levels of sustainable development practices. The paper also highlights the importance of focusing on building a sustainable workforce to achieve authentic and successful results, exploring the impact of corporate sustainability on the local and global community.

The obtained results in this study confirm the key role of corporate sustainability in the textile industry as an imperative to achieve a balance between corporate growth and social goals, especially sustainable development. Sustainability involves a holistic approach that encompasses environmental, social and economic aspects of textile production. This paper identifies critical success factors for corporate sustainability, with a particular focus on the positive correlation between sustainability and employee organisational commitment. Sustainable development practices, job satisfaction, motivation, corporate image, leadership and professional development play a key role in achieving this positive relationship. Overall, the paper provides a basis for further research and a contribution to the understanding of the importance of sustainability in the textile industry.

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The impact of AI-powered personalisation on consumer purchase decisions in the textile sector

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ABSTRACT – REZUMAT

The impact of AI-powered personalisation on consumer purchase decisions in the textile sector

In the context of accelerated digital transformation and shifting consumer expectations regarding online shopping experiences, digital marketing in the textile industry faces both significant challenges and emerging opportunities. This study investigates how artificial intelligence (AI) contributes to shaping consumer preferences by personalising commercial communication, generating relevant product recommendations, and automating interactions between brands and users.

By combining a literature review with primary data collected through a survey of 358 Romanian consumers active in digital environments, the research explores their perceptions of AI-driven online marketing. The results indicate that 61% of respondents view artificial intelligence as a helpful factor in their decision-making process, while 55% consider personalised recommendations to be relevant in selecting clothing products. At the same time, a substantial segment of users expresses concerns related to algorithmic transparency and the level of control offered.

The article proposes a conceptual model for integrating AI into digital marketing strategies, with a focus on personalising the shopping experience and influencing purchase intention. The findings support the need for data-driven, consumer-centred approaches that leverage automation to deliver added value in the textile industry through the use of advanced technologies.

Keywords: *consumer decision-making, algorithmic personalisation, digital user experience, data-driven marketing, customer trust in AI, textile retail innovation*

Impactul personalizării bazate pe inteligența artificială asupra deciziilor de cumpărare ale consumatorilor din sectorul textil

În contextul transformării digitale accelerate și al schimbării așteptărilor consumatorilor în ceea ce privește experiențele de cumpărături online, marketingul digital în industria textilă se confruntă atât cu provocări semnificative, cât și cu oportunități emergente. Acest studiu investighează modul în care inteligența artificială (IA) contribuie la modelarea preferințelor consumatorilor prin personalizarea comunicării comerciale, generarea de recomandări relevante de produse și automatizarea interacțiunilor dintre mărci și utilizatori.

Combinând o analiză a literaturii de specialitate cu date primare colectate printr-un sondaj realizat pe un eșantion de 358 de consumatori români activi în mediul digital, cercetarea explorează percepțiile acestora asupra marketingului online bazat pe IA. Rezultatele indică faptul că 61% dintre respondenți consideră inteligența artificială un factor util în procesul lor de luare a deciziilor, în timp ce 55% consideră recomandările personalizate relevante în selectarea produselor vestimentare. În același timp, un segment substanțial de utilizatori își exprimă îngrijorarea cu privire la transparența algoritmică și la nivelul de control oferit.

Articolul propune un model conceptual pentru integrarea IA în strategiile de marketing digital, cu accent pe personalizarea experienței de cumpărare și influențarea intenției de cumpărare. Rezultatele susțin necesitatea unor abordări bazate pe date și centrate pe consumator, care să utilizeze automatizarea pentru a oferi valoare adăugată în industria textilă prin utilizarea tehnologiilor avansate.

Cuvinte-cheie*: procesul decizional al consumatorilor, personalizarea algoritmică, experiența digitală a utilizatorilor, marketingul bazat pe date, încrederea clienților în IA, inovarea în comerțul cu amănuntul de textile*

INTRODUCTION

Online marketing has undergone an accelerated evolution over the past two decades, marking a clear transition from traditional “one-to-many” communication to personalised and adaptive approaches based on data analysis and machine learning. This shift has been enabled by the massive digitalisation of communication channels and the exponential growth of available data regarding user behaviour in digital environments [1]. In this context, content personalisation has become a central pillar of digital marketing strategies, particularly in industries such as textiles, where style preferences, aesthetics, and identity directly influence purchasing decisions.

Personalisation in digital marketing is defined as the process by which content, products, or services are adapted in real time to the behaviours, interests, or individual traits of a consumer [2]. Unlike classical segmentation, which involves grouping consumers into broad categories, personalisation enables a unique, user-specific approach based on historical data and the current interaction context [3]. This granular orientation increases consumer engagement, the perceived relevance of the message, and ultimately, the conversion rate [4].

In the textile industry specifically, personalisation has a high potential to influence consumer buying decisions. The selection of clothing items is often driven by emotional, aesthetic, and symbolic factors; consumers express their identity, status, and sense of belonging through fashion choices [5]. In this regard, an online shopping experience capable of recommending products based on past style preferences, colour, fit, or brand becomes a significant competitive advantage. Brands that invest in personalised recommendation engines, collaborative filtering algorithms, and tailored visual content are more likely to foster customer loyalty and improve conversion performance.

Technology enables personalisation at scale through the integration of CRM tools, intelligent e-commerce platforms, and AI systems. According to recent studies, online content personalisation can contribute to revenue increases of up to 20% in e-commerce compared to standard approaches [6]. Additionally, consumers who interact with personalised content spend more time on the site, have a higher likelihood of completing purchases, and are more likely to return.

In the fashion domain, personalisation extends beyond product suggestions to encompass the entire digital experience. For example, modern e-commerce platforms can adapt visual interfaces to user preferences, display models based on estimated customer morphology, or integrate intelligent filters that prioritise items aligned with a user's personal style. Furthermore, the use of augmented reality and virtual try-ons, customised to the consumer's digital avatar, represents the next frontier of personalisation in textile retail [7].

Despite its clear advantages, personalisation also raises challenges related to data privacy and technological acceptance. Research indicates that over-personalisation, perceived as intrusive, may lead to the opposite effect, diminished trust and even brand avoidance [8]. Therefore, personalisation strategies must be transparent, offer users control, and rely on informed consent.

GENERAL INFORMATION

Artificial Intelligence in digital marketing

Artificial Intelligence (AI) is one of the most transformative technologies of the 21st century, having a major impact on digital marketing practices. Through its capacity to process large volumes of data in real time, learn from behaviours, and automatically adapt strategies, AI is redefining how companies interact with the public, personalise content, and optimise commercial performance [9].

In marketing, AI is implemented through various applications targeting different stages of the customer relationship. Among the most common are personalised recommendation systems, which suggest products or services based on a user's past behaviour or similar customers. These algorithms, widely used on e-commerce and online retail platforms, contribute significantly to increasing average basket value and customer retention [10]. Typical examples include prompts such as "customers who bought this item also purchased…", generated by machine learning models based on frequent associations.

Another essential application of AI is content delivery automation. Through marketing automation systems, companies can send personalised emails, notifications, or banners based on user activity. For example, if a customer adds a product to their cart without completing the purchase, the system may automatically generate a limited-time discount offer to stimulate conversion. This contextual communication helps reduce cart abandonment and increases engagement [11].

Conversational chatbots based on natural language processing (NLP) are another prominent manifestation of AI in marketing. These tools interact with users in real time, answering frequently asked questions, offering recommendations, or assisting with the ordering process. Unlike early, basic versions, modern chatbots can understand user intent and generate coherent and natural responses [12]. In fashion retail, digital agents can be integrated into product pages to provide stock availability, sizing guides, or alternatives based on expressed preferences.

International fashion leaders such as Zara, H&M, and ASOS have already integrated advanced AI systems for automated styling, visual search, and micro-personalised recommendations at scale, demonstrating strong performance improvements across European markets. Similar trends are emerging globally, suggesting the universal relevance of AI-driven personalisation strategies in textile retail.

Sentiment analysis is also increasingly used in digital marketing campaigns. Through AI algorithms, brands can analyse user comments, reviews, and social media reactions to gauge overall attitudes toward a product or service. Based on this insight, advertising messages can be dynamically adjusted to reflect the appropriate tone, respond to criticism, or amplify positive feedback [13].

Empirical studies show that users are generally receptive to AI in digital environments as long as it offers tangible benefits, such as time savings, simplicity of the shopping experience, or access to more relevant products. According to Puntoni et al. [14], AI is perceived positively when it supports user autonomy and is not seen as invasive or manipulative.

However, the acceptance of AI is not universal. Some users express resistance, especially when they perceive a lack of transparency or a high level of automation that limits human control. Trust in technology becomes a key factor in the success of

AI-based marketing strategies. Brands must clearly communicate the role of these systems, offer customisation options, and avoid hyper-automation [15].

Consumer behaviour and AI

Consumer behaviour has always been shaped by a complex interplay of cognitive, emotional, social, and contextual factors. In the digital era, these traditional factors are now joined by interactions with intelligent systems, particularly those powered by artificial intelligence (AI), which directly influence decision-making processes and brand relationships [16].

Online consumers are exposed to an overwhelming number of options, often resulting in information saturation. In this environment, AI functions as a cognitive filter that reduces complexity by offering suggestions, anticipating needs, and personalising interactions based on a user's history and behaviours [9]. This process can lead to more efficient decision-making, time savings, and a smoother shopping experience.

However, the relationship between consumers and AI is mediated by a critical factor: trust in technology. Research indicates that consumers form a positive relationship with AI systems when the benefits are clear, and interactions are transparent, controllable, and predictable [14]. In contrast, a lack of transparency, excessive automation, or misuse of personal data can lead to resistance, anxiety, or even brand rejection [15].

In the textile industry specifically, purchasing decisions are often emotional and symbolic. Clothing fulfils not only a functional need but also contributes to self-expression, aesthetic preferences, and social integration [5]. Therefore, the integration of AI into fashion retail must be not only technological but also empathetic. Algorithms that can interpret stylistic preferences and offer recommendations aligned with a user's taste can strengthen brand trust and increase loyalty [17].

Another important element is the perception of control. When AI offers suggestions without limiting choices, consumers feel a sense of autonomy. On the other hand, when systems appear to "steer" decisions, psychological resistance may arise. Recent studies suggest that AI is more effective when it functions as a digital assistant rather than an invisible decision-maker [18].

Moreover, consumers vary in their willingness to accept AI. Digitally savvy younger users tend to adopt AI-based interactions more easily, while traditional users exhibit more scepticism, especially in the absence of clear explanations about system functionality [4]. Thus, the success of AI in influencing behaviour also depends on digital literacy and user familiarity with technology.

In the textile industry, where purchasing cycles are frequent yet impulsive, AI plays a key role in anticipating recurring needs. For example, by analysing purchase history and seasonal preferences, intelligent systems can recommend new collections or personalised discounts, increasing the likelihood of conversion. Additionally, in remarketing campaigns, AI enables message recalibration based on customer reactions, crucial in a sector driven by fast-changing trends and styles [13].

AI also contributes to the experiential aspect of shopping, an increasingly relevant factor for newer generations of consumers. Through augmented reality, friendly chatbots, or interactive video recommendations, AI transforms shopping from a simple transaction into an immersive experience, positively influencing brand perception [12].

In conclusion, consumer behaviour in the digital era is increasingly shaped by interactions with AI systems. In the textile industry, where decisions are emotional, visual, and taste-driven, AI has the potential to significantly enhance the decision-making process, provided it is implemented in a transparent, empathetic, and user-centred manner.

The proposed conceptual framework

Based on the relevant literature, we propose an integrated conceptual framework that describes how consumer perception of artificial intelligence (AI) indirectly influences the intention to purchase textile products through the perceived personalisation of marketing communication. Additionally, the model considers the role of trust in AI as a moderating variable in the relationship between personalisation and purchasing behaviour.

H1: Positive perception of AI (PAI) positively influences the perceived usefulness of AI (PU).

Consumer perception of AI is foundational to its acceptance. According to the Technology Acceptance Model (TAM), a positive attitude toward a system directly influences its perceived usefulness. In digital marketing, if AI is perceived as friendly, easy to use, and naturally integrated into the online experience, users are more likely to find it useful in decision-making [9]. In fashion retail, where choice overload is common, a favourable perception of AI leads to greater expectations for its value-added role.

H2: Perceived usefulness of AI (PU) positively influences perceived personalisation (PP).

The literature emphasises a strong link between perceived system usefulness and the level of personalisation users experience [2]. In e-commerce, AI is often valued for its ability to deliver content and recommendations tailored to individual needs. The more capable AI is of simplifying, filtering, or predicting consumer preferences, the greater the sense of personalisation [3]. In fashion retail, this relationship is magnified by expectations of stylistic fit, size guidance, and adaptive cross-selling.

H3: Perceived usefulness of AI (PU) positively influences trust in AI (TAI).

Trust in AI is largely shaped by consumer experience and assessment of system performance. When AI is perceived as helpful, saving time, reducing cognitive effort, and delivering relevant outcomes, consumers are more inclined to trust it [15]. Marketing research confirms that perceived usefulness not only boosts adoption but also functional trust, especially when AI recommendations and predictions are validated over time [14].

H4: Perceived personalisation (PP) positively influences brand engagement (BE).

Personalised marketing enhances the relevance and depth of the brand–consumer relationship. When content, offers, and communication align with individual needs and preferences, consumers feel understood, increasing satisfaction and involvement [1], [4]. In the textile industry, where style choices are deeply personal, personalisation becomes a key driver of brand loyalty.

H5: Trust in AI (TAI) positively influences brand engagement (BE).

In digital environments, trust extends not only to the brand but also to the technologies it employs. When AI is perceived as trustworthy, delivering accurate recommendations, respecting privacy, and avoiding intrusiveness, it positively impacts consumer perceptions of the associated brand [15]. Research shows that brands that transparently communicate how AI is used and offer users control over data create stronger emotional and attitudinal engagement [17].

H6: Brand engagement (BE) positively influences purchase intention (PI).

Brand engagement is a strong predictor of purchasing behaviour, according to brand attachment theory [19]. A consumer who feels emotionally connected or personally identified with a brand is more likely to make repeat purchases and express favourable intentions. In the fashion sector, this is amplified by the expressive nature of clothing, linking consumption choices with personal identity.

H7: Perceived personalisation (PP) positively influences purchase intention (PI).

Personalisation is often positively correlated with conversion and purchase intention. Consumers are more likely to buy when they feel the offer is tailored to them and the options meet their expectations [8]. In fashion retail, personalisation boosts confidence in the buying decision, especially when uncertainty exists around fit, aesthetics, or style.

H8: Trust in AI (TAI) moderates the relationship between perceived personalisation (PP) and purchase intention (PI).

Even if personalisation is perceived positively, its effectiveness in generating purchase intent depends on the level of trust in the technology behind it. When AI is seen as unreliable, invasive, or inaccurate, consumers may dismiss even highly relevant recommendations [18]. Thus, trust in AI acts as an amplifying or dampening factor, reinforcing the causal link between personalisation and purchase behaviour.

MATERIALS AND METHODS

The primary objective of this study is to analyse how artificial intelligence (AI), when applied in digital marketing, influences consumer purchasing behaviour in the textile industry. The research focuses specifically on the relationships between consumers' perceptions of AI, perceived personalisation, trust in technology, brand engagement, and purchase intention. To address the stated objectives and test the proposed hypotheses, a quantitative approach was employed, based on primary data collected through an online questionnaire.

This study adopts a quantitative, descriptive, and explanatory research design, aimed at identifying and quantifying the relationships among the variables under investigation. The descriptive dimension allows for the characterisation of digital consumer profiles who interact with AI technologies in the context of online shopping, while the explanatory dimension aims to test the direct, mediated, and moderated effects among the variables in the conceptual model.

The research follows a cross-sectional design, with data collected over a clearly defined period. No experimental manipulation was involved; instead, the study relied on passive observation of respondents' self-reported perceptions.

Research instrument

The Data collection was conducted through a self-administered online questionnaire, distributed via social media platforms, consumer forums, and communities interested in fashion and e-commerce. The data collection period spanned from April to June 2025.

The questionnaire was structured into six main sections, each corresponding to one of the key constructs analysed in the model:

- Demographics: gender, age, education level, frequency of online purchases;
- Familiarity with AI: previous interactions with AI technologies in e-commerce (e.g., chatbots, intelligent recommendations, personalised ads);
- Perception of AI: measured through items evaluating perceived usefulness, clarity, adaptability, and contribution to the shopping experience (5 items, 5-point Likert scale);
- Perceived personalisation: extent to which messages, offers, and products are tailored to individual preferences (4 items, 5-point Likert scale);
- Trust in AI: measured through trust in automated recommendations, perceived control, and transparency (4 items);
- Brand engagement: assessed through willingness to continue interaction with the brand, loyalty, and emotional attachment (3 items);
- Purchase intention: self-reported willingness to purchase textile products based on personalised AI recommendations (3 items).

A pilot test was conducted on a sample of 30 respondents to validate the structure and wording of the questionnaire. Feedback from the pilot was used to clarify certain terms and optimise the overall length and clarity of the instrument. To ensure the authenticity and quality of responses, two attention-check items were included, and responses exhibiting inconsistent patterns or extremely short completion times were removed. The survey platform also restricted multiple submissions from the same device/IP address. A pilot pre-test (N=30) confirmed respondent understanding of item wording and structure, ensuring content validity.

Sample characteristics

A non-probability, convenience sampling method was employed, resulting in a final sample of 358 Romanian respondents, selected based on the following two criteria:

- Participants had made at least one online clothing purchase in the past six months;
- Participants had interacted with at least one AI functionality (e.g., automated recommendation or chatbot).

Key demographic characteristics of the sample include:

- Gender: 63% female, 37% male;
- Age: 58% between 25 and 44 years old;
- Education: 81% with higher education;
- Frequency of online purchases: 66% reported shopping for clothing online at least once a month.

These demographic indicators reflect an urban, digitally engaged consumer base, well-aligned with the study's focus on emerging technologies in retail. Detailed descriptive statistics are presented in table 1, reflecting the diversity of respondents in terms of demographic and behavioural purchasing characteristics.

The distribution confirms the relevance of the sample for digital textile commerce research.

Data analysis methods

To test the proposed conceptual model, the WarpPLS 8.0 software was employed, which is specifically designed for Partial Least Squares Structural Equation Modelling (PLS-SEM). This methodological approach was chosen for its ability to handle complex models involving multiple causal relationships, latent variables, and both mediating and moderating effects [20].

Moreover, PLS-SEM is particularly suited for exploratory studies with moderately sized samples and non-normal data distributions, conditions that are met in the current research context.

The quality of the structural relationships is confirmed by the value of the Average Path Coefficient (APC), which is 0.389 with a high level of statistical significance (p<0.001). This value, exceeding the recommended threshold of 0.30, indicates a consistent connection between the model variables and supports the validity of the theoretical causal relationships. Additionally, the Average R-squared (ARS = 0.342) and Average Adjusted R-squared (AARS = 0.340) coefficients demonstrate that the model explains, on average, over 34% of the variance in the dependent constructs. This level of explanatory power is considered moderate to high in consumer behaviour studies [20], suggesting satisfactory predictive capability.

With respect to the global validity of the model, the Tenenhaus Goodness-of-Fit (GoF) index is 0.418, surpassing the threshold of 0.36, which is regarded as "large" according to the relevant literature [21]. This value indicates a strong alignment between the theoretical model structure and the empirical data collected, thus offering solid evidence for the robustness of the proposed framework.

Table 1

DEMOGRAPHIC AND SHOPPING BEHAVIOUR DISTRIBUTION OF RESPONDENTS		
Variable	**Categories**	**Percentage (%)**
Gender	Female / Male	63% / 37%
Age	18–24 / 25–34 / 35–44 / 45+	22% / 34% / 24% / 20%
Geographic area	Urban / Rural	78% / 22%
Monthly income	<600€ / 600–1000€ / >1000€	32% / 45% / 23%
Online clothing purchase frequency	Monthly / Quarterly / Rarely	66% / 22% / 12%
Clothing categories purchased	Casual / Sportswear / Business / Luxury	72% / 41% / 28% / 9%

Average path coefficient (APC)=0.389, P<0.001
Average R-squared (ARS)=0.342, P<0.001
Average adjusted R-squared (AARS)=0.340, P<0.001
Average block VIF (AVIF)=1.292, acceptable if <= 5, ideally <= 3.3
Average full collinearity VIF (AFVIF)=1.804, acceptable if <= 5, ideally <= 3.3
Tenenhaus GoF (GoF)=0.418, small >= 0.1, medium >= 0.25, large >= 0.36
Simpson's paradox ratio (SPR)=1.000, acceptable if >= 0.7, ideally = 1
R-squared contribution ratio (RSCR)=1.000, acceptable if >= 0.9, ideally = 1
Statistical suppression ratio (SSR)=1.000, acceptable if >= 0.7
Nonlinear bivariate causality direction ratio (NLBCDR)=1.000, acceptable if >= 0.7

Fig. 1. Global Model Fit and PLS-SEM quality indicators

Regarding collinearity and internal consistency, the very low values of the Average Variance Inflation Factor (AVIF = 1.292) and the Average Full Collinearity VIF (AFVIF = 1.804) confirm the absence of significant multicollinearity among latent constructs. These values fall well below the critical threshold of 3.3, indicating good independence between variables and reliability in the estimation of regression coefficients.

The stability and coherence of the model are further supported by four additional indicators, each achieving the ideal value of 1.000: the Simpson's Paradox Ratio (SPR), R-squared Contribution Ratio (RSCR), Statistical Suppression Ratio (SSR), and the Nonlinear Bivariate Causality Direction Ratio (NLBCDR). These results show that the model is not affected by statistical paradoxes or suppressor effects and that the identified causal relationships are coherent, directional, and robust. Each variable contributes in a positive and theoretically consistent manner to explaining the analysed consumer behaviour.

Overall, the set of statistical indicators confirms that the proposed model is appropriate for investigating the studied phenomenon, both in terms of the quality of internal relationships and its explanatory power and structural coherence.

RESULTS

The structural model analysis conducted using WarpPLS 8.0 aimed to test the eight hypotheses formulated in the conceptual framework by evaluating the strength and statistical significance of the relationships between latent variables. The results confirm the internal consistency of the theoretical model and offer empirical support for the assumed causal relationships.

R2 – Model's explanatory power

The R^2 coefficients reflect the proportion of variance in the dependent variables explained by their predictors:

- Perceived Usefulness of AI (UP): $R^2 = 0.17 \rightarrow 17\%$ of the variation in perceived usefulness is explained by the consumer's perception of AI.
- Perceived Personalisation (PP): $R^2 = 0.46 \rightarrow 46\%$ of the variation in perceived personalisation is explained by perceived usefulness.
- Trust in AI (IAI): $R^2 = 0.15 \rightarrow 15\%$ of the variation in trust is explained by perceived usefulness.
- Brand Engagement (AB): $R^2 = 0.49 \rightarrow$ Nearly half of the variation in brand engagement is explained by personalisation and trust.
- Purchase Intention (IC): $R^2 = 0.44 \rightarrow 44\%$ of the variation in purchase intention is explained by personalisation, trust, and engagement.

These values indicate good explanatory power, particularly in the context of digital marketing research [20].

Path coefficients interpretation (β)

- H1: PAI → UP ($\beta=0.41$, $p<0.01$) A positive perception of AI has a significant and moderate effect on perceived usefulness, confirming that a favourable image of AI leads to more functional evaluations.
- H2: UP → PP ($\beta=0.40$, $p<0.01$) Perceived usefulness has a strong positive effect on perceived personalisation. Users who find AI useful tend to perceive the marketing communication as more tailored.
- H3: UP → IAI ($\beta=0.39$, $p<0.01$) When AI is considered useful, it fosters consumer trust, supporting the hypothesis that functional perceptions enhance cognitive attachment.
- H4: PP → AB ($\beta=0.57$, $p<0.01$) The relationship between perceived personalisation and brand engagement is very strong and statistically significant – one of the most important in the model.
- H5: IAI → AB ($\beta=0.24$, $p<0.01$). Trust in AI has a significant positive impact on brand engagement, though weaker than personalisation. It still supports H5.
- H6: AB → IC ($\beta=0.18$, $p<0.01$) Brand engagement has a direct but relatively weak influence on purchase intention, suggesting a mediated effect.
- H7: PP → IC ($\beta=0.30$, $p<0.01$) Perceived personalisation has a significant positive impact on purchase intention, highlighting the importance of tailored content in driving e-commerce conversion.
- H8: IAI → IC ($\beta=0.56$, $p<0.01$) Trust in AI is the strongest direct predictor of purchase intention, emphasising the critical role of technology in shaping buying behaviour.

Hypothesis validation

All eight hypotheses (H1–H8) were statistically confirmed at the $p<0.01$ level. The path coefficients (β) indicate both the direction and intensity of the proposed theoretical relationships. Notably, H4 (PP → AB)

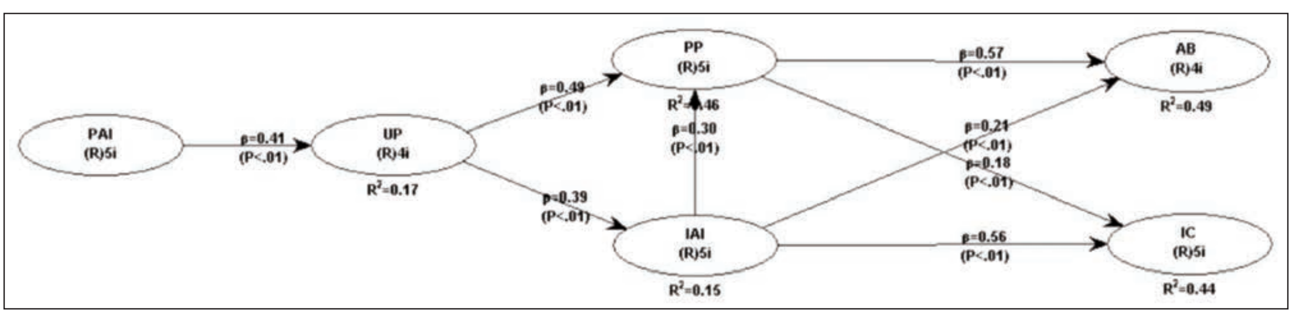

Fig. 2. The proposed conceptual model

and H8 (IAI → IC) recorded the highest effect sizes, suggesting that personalisation and trust in AI are essential drivers of consumer behaviour in the textile e-commerce context.

Construct reliability and validity

To build the latent variables included in the research model, defining items were derived from the questionnaire administered to respondents. Data analysis and interpretation were conducted using WarpPLS 8.0, a software specialised in estimating Partial Least Squares Structural Equation Models (PLS-SEM). WarpPLS is particularly recommended for empirical studies involving complex relationships between latent constructs, and it excels in handling non-normal data distributions and moderate to small samples [22].

The quality of measurement was assessed using standard reliability and convergent validity indicators: Composite Reliability (CR), Cronbach's Alpha, and Average Variance Extracted (AVE).

As shown in table 2, all constructs demonstrate composite reliability values above the 0.70 threshold (ranging from 0.777 to 0.896), indicating satisfactory internal consistency. Cronbach's Alpha values also fall within acceptable limits, ranging from 0.618 (UP) to 0.855 (IC), reflecting good internal coherence of the measurement items.

Average Variance Extracted (AVE) values range from 0.467 to 0.634. Most constructs exceed the 0.50 threshold, which is considered acceptable for convergent validity [20]. These results confirm that the latent variables adequately explain the variance of their respective indicators.

Discriminant validity was tested using the Fornell-Larcker criterion, which requires that the square root of each construct's AVE exceeds the inter-construct correlations. As shown in table 3, all diagonal values (in parentheses) are higher than the corresponding correlations, confirming discriminant validity.

These results validate both the measurement reliability and the theoretical distinctiveness of the constructs. Following Kock (2020) [22], the use of AVE and inter-construct correlations confirms that there are no 1:1 relationships between the analysed variables and that the items used reliably reflect the theoretical concepts proposed in the model.

In summary, the measurement instrument used in this study is both reliable and valid, enabling a rigorous and coherent interpretation of the relationships among the variables in the proposed model.

CONCLUSIONS

This study aimed to explore how artificial intelligence (AI), when applied to digital marketing, influences consumer purchase behaviour within the textile industry. Through an empirically validated conceptual model, the research identified significant relationships between positive perceptions of AI, perceived usefulness, online experience personalisation, trust in technology, brand engagement, and purchase intention.

The findings confirm that favourable perceptions of AI lead to an increase in perceived usefulness, which in turn positively influences both perceived personalisation and trust in AI technologies. Personalisation has a direct and substantial effect on brand engagement, while trust in AI emerges as the strongest direct predictor of purchase intention. Moreover, the effect of personalisation on purchase intention is further strengthened through the mediating role of engagement and the moderating effect of trust, illustrating a

Table 2

RELIABILITY AND VALIDITY OF LATENT CONSTRUCTS

Construct	Composite reliability	Cronbach's Alpha	AVE
PAI (Perception of AI)	0.833	0.749	0.503
UP (Perceived usefulness)	0.777	0.618	0.467
PP (Perceived personal)	0.825	0.732	0.493
AB (Brand engagement)	0.776	0.615	0.469
IC (Purchase intention)	0.896	0.855	0.634
IAI (Trust in AI)	0.834	0.750	0.504

Table 3

INTER-CONSTRUCT CORRELATIONS AND SQUARE ROOTS OF AVE

	PAI	UP	PP	AB	IC	IAI
PAI	(0.709)	0.372	0.316	0.323	0.271	0.314
UP	0.372	(0.684)	0.561	0.554	0.314	0.389
PP	0.316	0.561	(0.702)	0.665	0.447	0.479
AB	0.323	0.554	0.665	(0.685)	0.511	0.490
IC	0.271	0.314	0.447	0.511	(0.796)	0.620
IAI	0.314	0.389	0.479	0.490	0.620	(0.710)

complex and interdependent dynamic between the variables studied.

The model, tested using WarpPLS 8.0, demonstrated a good level of explanatory power (GoF = 0.418) and significant relationships between constructs (APC = 0.389, $p<0.001$), with all hypotheses statistically validated. These results provide strong empirical support for the digital marketing literature and highlight the importance of integrating AI into consumer-centred marketing strategies.

From a practical standpoint, the conclusions of this study can be utilised by textile industry brands seeking to develop personalised marketing strategies based on intelligent algorithms. Effective personalisation, supported by transparent and trustworthy AI technologies, can strengthen customer relationships and increase conversion rates in the digital environment.

On a theoretical level, the study contributes to a better understanding of the complex relationships between technology, psychological perceptions, and consumer behaviour, offering an integrated and empirically tested conceptual framework within the Romanian market context.

Managerial implications

The findings highlight several strategic priorities for textile brands:

- Ensure algorithmic transparency by clearly informing users how recommendations are generated;
- Provide users with control options (opt-in personalisation, adjustable preferences, privacy settings);
- Avoid intrusive or overly persistent personalisation to protect user trust;
- Adapt AI communication styles based on consumers' digital literacy and adoption readiness;
- Leverage trust signals (explainable AI, secure data handling, GDPR compliance) to strengthen credibility.

Given the strong relationship between trust in AI and purchase intention ($\beta = 0.56$), small increases in trustworthiness can generate meaningful improvements in conversion rates for online textile retailers.

Limitations and future research directions

While the findings make a valuable contribution to the understanding of how artificial intelligence influences consumer behaviour in the context of digital marketing within the textile industry, several limitations should be acknowledged, and they offer directions for future research.

The first limitation concerns the non-probabilistic, convenience-based sample, which restricts the generalizability of the findings to the broader population. Although the sample size (N = 358) is appropriate for PLS-SEM analysis, future studies could benefit from larger, probabilistic samples to produce more representative results at national or international levels.

Additionally, as the sample is restricted to Romanian consumers, cultural and market-specific factors may influence generalizability to other countries. Future comparative studies across different European and international markets would provide a broader understanding of how cultural context shapes consumer responses to AI personalisation.

Secondly, the cross-sectional design of the study prevents the establishment of robust causal relationships over time. Longitudinal research could provide deeper insights into how consumer perceptions of AI evolve and how purchasing intentions change in response to technological developments.

Thirdly, the reliance on self-reported data introduces potential cognitive biases (e.g., social desirability, overestimation of AI familiarity). Future research should consider incorporating behavioural data (such as clickstream analytics, engagement metrics, or conversion funnels) to enhance objectivity and accuracy.

Another limitation is that the proposed model was tested exclusively within the textile sector. While this industry is highly relevant for the study of AI-driven personalisation, the findings may differ across other sectors such as FMCG, financial services, or digital tourism. Cross-industry comparisons could reveal important consumer differences in their receptiveness to intelligent technologies.

Future research directions include:

- Extending the conceptual model by incorporating new variables, such as privacy attitudes, information overload, perceived brand equity, or user experience (UX).
- Conducting cross-national comparisons of AI's effects in digital marketing to explore cultural differences in technology adoption.
- Integrating qualitative methods (e.g., in-depth interviews, discourse analysis) to gain a more nuanced understanding of trust and resistance toward AI.
- Experimentally testing different types of AI-driven personalisation (visual, textual, behavioural) to isolate their specific impact on purchasing decisions.

By addressing these avenues, future studies can deepen our understanding of the human–technology interaction in digital marketing and provide more effective strategies for brands aiming to optimise consumer engagement in online environments.

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Design of an antibacterial medical face mask with oleuropein additive

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ABSTRACT – REZUMAT

Design of an antibacterial medical face mask with oleuropein additive

This study seeks to develop a protective mask infused with oleuropein to ensure excellent defence against bacteria and viruses. The mask features a three-layer construction, with the inner and outer layers composed of PP spunbond nonwoven fabric, while the centre layer consists of PP (polypropylene) meltblown nonwoven fabric. The leaves of olive trees in the Antalya region are harvested, air-dried, and subsequently pulverised into fine particles. Ground olive particles are removed utilising a Soxhlet apparatus. The extracted material is treated with a mask cloth using a method called "soak-hold-dry", and then it is tested for antibacterial activity according to the AATCC 147 standard. Staphylococcus aureus bacteria are selected to represent the gram-positive group, while Escherichia coli bacteria represent the gram-negative group. The zone diameters are measured at 47 mm for S. aureus and 40 mm for E. coli. The findings indicated that fabrics infused with olive leaf extract, which contains oleuropein, exhibit significant antibacterial efficacy. The average bacterial filtering effectiveness of masks without an oleuropein additive is 96.7%, but masks with an oleuropein ingredient have an efficiency of 98.5%. The mean breathability rose from 3.7 mm H_2O to 4.8 mm H_2O. This data indicates that the breathability performance diminished with the addition of oleuropein.

Keywords: *olive leaf, antibacterial activity, face mask, oleuropein*

Proiectarea unei măști medicale antibacteriene cu adaos de oleuropeină

Acest studiu urmărește să dezvolte o mască de protecție impregnată cu oleuropeină, pentru a asigura o apărare excelentă împotriva bacteriilor și virusurilor. Masca are o structură cu trei straturi, straturile interioare și exterioare fiind compuse din nețesut PP consolidat la filare, iar stratul central din material nețesut PP (polipropilenă) de tip meltblown. Frunzele de măslin din regiunea Antalya sunt recoltate, uscate la aer și apoi pulverizate în particule fine. Particulele de măsline măcinate sunt îndepărtate utilizând un aparat Soxhlet. Materialul extras este tratat cu un material textil pentru măști utilizând o metodă numită „impregnare-menținere-uscare", iar apoi este testat pentru activitate antibacteriană în conformitate cu standardul AATCC 147. Bacteriile Staphylococcus aureus sunt selectate pentru a reprezenta grupul gram-pozitiv, în timp ce bacteriile Escherichia coli reprezintă grupul gram-negativ. Diametrele zonelor sunt măsurate la 47 mm pentru S. aureus și 40 mm pentru E. coli. Rezultatele au indicat faptul că materialele textile infuzate cu extract de frunze de măslin, care conține oleuropeină, prezintă o eficacitate antibacteriană semnificativă. Eficacitatea medie de filtrare a bacteriilor în cazul măștilor fără aditiv de oleuropeină este de 96,7%, dar măștile cu ingredientul oleuropeină au o eficiență de 98,5%. Respirabilitatea medie a crescut de la 3,7 mm H_2O la 4,8 mm H_2O. Aceste date indică faptul că performanța respirabilității a scăzut odată cu adăugarea de oleuropeină.

Cuvinte-cheie*: frunză de măslin, activitate antibacteriană, mască facială, oleuropeină*

INTRODUCTION

Recently, there has been a notable surge in studies focused on the creation of medicinal antibacterial and antiviral fabrics [1]. This study sought to develop a face mask that establishes an efficient barrier against bacteria and viruses during and subsequent to the COVID-19 pandemic. Therefore, if the mask surface becomes contaminated, it will reduce and eliminate the viability of bacteria and viruses. Numerous prior investigations have demonstrated the antibacterial, antiviral, and antifungal properties of the compound oleuropein. The literature review indicates that oleuropein is present in high concentrations in olive leaves [2, 3].

The coronavirus (COVID-19), which originally emerged in Wuhan, China, in January 2019, has evolved into a global pandemic and has become the foremost challenge facing humanity today. Furthermore, research indicates that COVID-19 will not be the final virus to impact the globe. Consequently, humanity must contend with and manage bacteria and viruses. The significance of masks has been increasingly apparent in this conflict. The primary mask types advised for the COVID-19 pandemic are "Medical Face Mask–Surgical Mask", "FFP2/FFP3 (Filtering Face Piece) Non-vented Masks", and "FFP2/FFP3 Valve Masks". FFP2/FFP3 valveless masks and FFP2/FFP3 valve masks are predominantly utilised by healthcare professionals (table 1) [4].

Nonetheless, beyond medical applications, the utilisation of masks for public health has become an obligatory and essential precaution. The masks utilised by the public are referred to as "medical face masks" or "surgical masks". Surgical masks are composed of

Table 1

CLASSIFICATION OF MASKS [4]			
Function	**Medical face mask**	**FFP2/FFP3 Mask without valve**	**FFP2/FFP3 Valve mask**
Protecting the user	X	✓	✓
Protecting the environment	✓	✓	X
Standards	EN 14683	EN 149-A1 (EN 14683)	EN 149-A1

three distinct layers. The exterior and inner layers are composed of polypropylene non-woven fabric manufactured using the spunbond process, and the central layer is made of polypropylene (PP) non-woven fabric produced by the meltblown technique. The three layers are combined to form a mask (figure 1) [4].

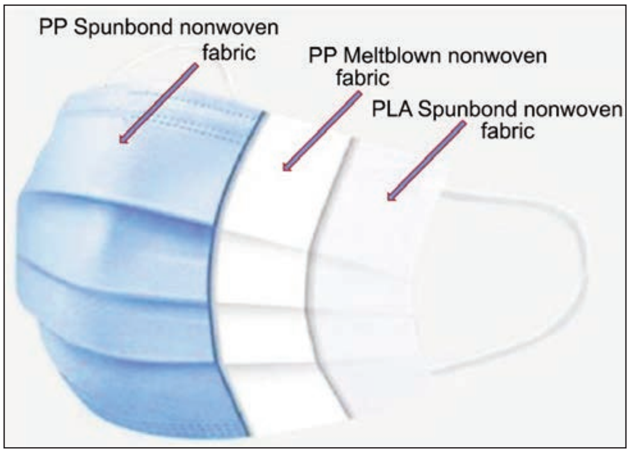

Fig. 1. Three-layer surgical mask made of PP non-woven fabric [4]

Medical face masks are categorised into three classifications: Type I, Type II, and Type III, in accordance with the EN 14683 standard (table 2). According to ASTM F 2100-07, masks fall into three categories: “low-level barrier”, “medium-level barrier”, and “high-level barrier” (table 2). Type-I masks, preferred by the public versus FFP-type masks, can cause skin problems like allergies, diaper rash, and acne in certain skin types and fail to provide 95% protection against viruses. Furthermore, another drawback of these masks is that they emit an odour of breath after several hours of use. The inspiration for this study stems from the design of a new mask intended to address the issues associated with “Type-I medical face masks”.

Numerous studies in the literature have examined medical face masks that incorporate additives such as silver, copper, lignin, chitosan, etc. The middle layer of the mask is dipped in the solution containing lignin/copper nanoparticles for 24 hours and then dried to evaluate the antibacterial activity. The mask coated with lignin/copper nanoparticles showed no cytotoxicity and killed microbes by destroying cell membranes [6]. In another study, researchers looked at how well silver nanoparticle-sodium alginate and chitosan nanocomposite films can fight bacteria in acne treatment, and they found that these films created clear areas free of bacteria that were between 12.33 mm and 13.67 mm wide against *S. aureus, E. coli*, and *C. acnes* bacteria [7].

The mask utilised in this investigation is produced by impregnating olive leaf extract onto a three-layer fabric composed of nonwoven polypropylene materials. According to the results of the investigations, the oleuropein compound that is extracted from olive leaves is a naturally occurring chemical that possesses antifungal, antiviral, and antibacterial qualities. Studies have indicated that the oleuropein chemical offers 99% viral prevention.

Olive leaf has been utilised in traditional medicine for generations. For example, the 1800s recognised its use in combating the malaria epidemic. The American

Table 2

CLASSIFICATION OF SURGICAL MASKS ACCORDING TO EN 14683 AND ASTM F 2100 [5]						
Test	**EN 14683**			**ASTM F2100**		
	Type I	**Type II**	**Type IIR**	**Level 1**	**Level 2**	**Level 3**
Bacterial filtration efficiency (%)	≥95	≥98	≥98	≥95	≥98	≥98
Differential pressure mm (H_2O/cm^2) (Pa/cm^2)	<3.0 <29.4	<3.0 <29.4	<5.0 <49.0	<4.0 <39.2	<5.0 <49.0	<5.0 <49.0
Sub-micron particulate filtration efficiency at 0.1 micron (%)	Not required	Not required	Not required	≥95	≥98	≥98
Splash resistance/Synthetic blood resistance (mmHg pass result)	Not required	Not required	120 (16.0 kPa)	80	120	160
Flame spread	Not required	Not required	Not required	Class 1	Class 1	Class 1
Microbial cleanliness (cfu/g)	≤30	≤30	≤30	Not required	Not required	Not required

Cancer Research Institute has declared that olive leaf is the preeminent natural antibacterial and antiviral plant of the 21st century [8, 9]. Moreover, numerous studies indicate that oleuropein may be effective against HIV, parainfluenza type 3 virus, herpes mononucleosis, hepatitis virus, rotavirus, bovine rhinovirus, canine parvovirus, and feline leukaemia virus [10, 11].
The American Food and Drug Administration (FDA) has sanctioned the use of 29 medications containing oleuropein in the battle against the coronavirus. 97% of the world's olive trees are in the Mediterranean region, specifically in Spain, Italy, Greece, Türkiye, and Tunisia, as well as in nations like Portugal and Syria. The olive tree proliferates naturally in the maquis vegetation of these nations and has extensive distribution. In Türkiye, the extraction of oleuropein from olive leaves and its subsequent use are crucial for scientific research [2]. In all these nations, solely the fruit of olive trees is collected.
Nonetheless, its leaves possess significant value and can be transformed into a product that yields economic revenue. The leaves, a by-product, are generated during the trimming of the trees, the harvesting of olives, and the cleaning and blending operations involved in olive oil production.
Oleuropein, derived from olive leaves, has been researched for its applications and utilised as a medicinal agent in the medical profession.
Nonetheless, the utilisation of oleuropein on textile materials for its antiviral, antibacterial, and antifungal characteristics has not been investigated too far. Phenolic compounds present in olive leaves include secoiridoids (oleuropein, dimethyloleuropein, verbascoside, ligtroside, and oleuroside), phenolic acids and their derivatives (vanillic acid, caffeic acid, and vanillin), phenolic alcohols (tyrosine and hydroxytyrosol), flavones (lutozeoline-7-glycoside, diosmetin-7-glycoside, luteolin, and diosmetin), flavonoids (quercetin, isorhamnetin, and rutin), and flavanols (catechin and gallocatechin) [12, 13].
Oleuropein is the predominant phenolic component found in olive leaves. This is succeeded by hydroxytyrosol, luteolin, apigenin flavone-7-glycosides, and verbascoside. Analysis of oleuropein content in olive leaves reveals that the concentration in the dried leaves of 14 olive trees ranged from 9.0% to 14.3% [14].

MATERIAL AND METHOD

Procurement of olive leaves and oleuropein compound

The oleuropein utilised in the project is sourced from olive leaves harvested from olive trees in the Mediterranean region. Subsequent to the drying of these leaves, they are subjected to extraction via a Soxhlet apparatus. The extracted sample is analysed using the HL-PC instrument to quantify its oleuropein content.

Provision of mask fabric

Non-woven materials are typically favoured for surgical masks. These fabrics are favoured because of their superior performance in bacteria filtering and air permeability compared to woven materials. The primary raw material for nonwoven fabrics is mostly polypropylene (PP) [15]. The masks have an inner and outer layer made from PP nonwoven fabric produced by the spunbond process, and the middle layer is made from PP nonwoven fabric created using the meltblown technique. The fabrics for the mask in the project are sourced from a mask manufacturing company.

Identification of bacteria

At the outset, it is important to emphasise the following points. The initiative aims to utilise bacteria from the respiratory tract. Due to the hazardous nature of testing these bacteria and the requirement for authorisation, a generalisation is employed, utilising *S. aureus* and *E. coli* to symbolise gram-positive and gram-negative bacteria, respectively. The personnel of Mehmet Akif Ersoy University Microbiology Laboratory facilitated the bacterial testing conducted. Research on oleuropein indicates its efficacy against several fungi, bacteria, and viruses. Oleuropein has demonstrated antiviral efficacy against mononucleosis herpes, hepatitis viruses, rotaviruses, bovine viruses, parvoviruses in canines, and leukaemia viruses in felines [16].
Numerous taste compounds exhibit antibacterial properties against *Staphylococcus aureus, Streptococcus mutans, Escherichia coli, Candida utilis*, and *Aspergillus niger* [17]. Olive leaf exhibits inherent resistance to microbes and insect infestations [18]. Initial documentation of its therapeutic properties as an antipyretic dates back to 1854, and subsequent reports of its antihypertensive and antibacterial actions follow [19].
Certain research indicates that olive leaves are abundant in phenolic compounds and α-tocopherol. The main phenolic compounds found in olive leaves are oleuropein, luteolin, luteolin-7-glucoside, apigenin, apigenin-7-glucoside, hydroxytyrosol, chlorogenic acid, p-coumaric acid, and rutin (quercetin-3-rutinoside) [20]. Research indicates that phenolic compounds in olive fruits and leaves exhibit inhibitory and retarding effects on microbial development.
Additionally, olive leaf extract possesses antioxidant properties [19] and serves as a potential source of antifungal agents, making it applicable as an additive in both the food and pharmaceutical industries [18].

Acquisition of olive leaf extract

Olive leaves are disseminated and desiccated at ambient temperatures for 15 days. The desiccated leaves are pulverised in a grinder and reduced to diminutive fragments. The leaves, reduced into minute fragments, are weighed on a precision scale and prepared for extraction (figure 2).

Fig. 2. Dehydrating and pulverising the olive leaves

The literature review revealed that the solid-liquid extraction process is employed to extract some components from natural plants, utilising an apparatus known as the “Soxhlet Extractor”. Consequently, the Soxhlet Extractor is employed to extract the oleuropein compound from pulverised olive leaves (figure 3).

Fig. 3. Extraction of olive leaves with Soxhlet device (Burdur Mehmet Akif Ersoy University)

Extraction is conducted using a Soxhlet apparatus as outlined below. The dried leaves, chopped into minute fragments, are weighed and placed into the cellulose extraction cartridge. The cartridge is, moreover, situated within the extraction arm. A chemical solvent is added to the glass flask and subsequently evaporated using a heater. The evaporating solvent ascends to the reflux via the extraction column. The solvent, concentrated in the rear cooler, flows to the extraction arm, dissolving the substance in the cartridge before returning to the glass flask. This technique is perpetually reiterated to finalise the extraction. The isolated compound is gathered in the flask. The residual solvent in the flask is eliminated, yielding the component to be extracted in its pure form [12].

Quantification of oleuropein concentration in olive leaf extract using High-Performance Liquid Chromatography (HPLC)

The concentration of oleuropein in the extract is quantified using the HPLC apparatus at Süleyman Demirel University Laboratory. 10.7 mg of the extract is mixed with 1 ml of methanol (figure 4), then diluted 20 times, and tested with the HPLC machine to measure the amount of oleuropein. The characteristics of the Shimadzu HPLC device are Detector: DAD detector (λmax = 278 nm), Autosampler: SIL-10ADvp, System Controller: SCL-10Avp, Pump: LC-10ADvp, Degasser: DGU-14A. Column oven: CTO-10Avp Agilent Eclipse XDB-C18 Column (250 × 4.60 mm) 5 microns Mobile phase: A: 3% acetic acid; B: methanol. Flow Rate: 0.8 ml per minute.

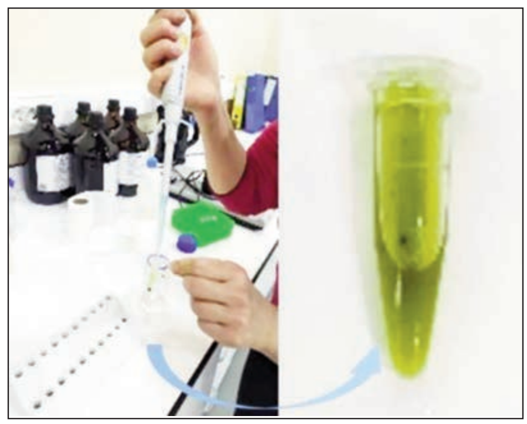

Fig. 4. Dissolving the extract in methanol

Absorption of olive leaf extract in nonwoven fabrics

The application of oleuropein extract to the three-layer mask fabric is conducted using the “soak-dry-hold” method [21]. Methanol serves as a solvent in the impregnation procedure. A 5% citric acid solution is utilised to bind the 20% extract to the mask fabric. The solution’s temperature is set to 35 °C and pH 5. The impregnation process is conducted for 25 minutes utilising a hot magnetic stirrer at a liquor ratio of 1:20. The solution-saturated fabric is subjected to 70% pressure in a laboratory squeezing machine to eliminate excess solution. The fabrics are maintained in the oven at 40 °C for a duration of 10 minutes for drying purposes.

Evaluation of antibacterial efficacy of extract-infused fabric

The antibacterial activity of the fabric infused with olive leaf extract was evaluated using the AATCC 147 test technique. The AATCC 147 diffusion agar method is a widely utilised standard for assessing the

Table 3

CLASSIFICATION OF SURGICAL MASKS ACCORDING TO ASTM F 2101 AND MIL-M-36954 C STANDARDS [23]			
Scale	**Level 1 barrier**	**Level 2 barrier**	**Level 1 barrier**
MIL-M-36954 C: ΔP (Breathability)	<4 mm H_2O	<5 mm H_2O	<5 mm H_2O
ASTM F2101: BFE (Filtration 3 μm)	≥% 95	≥% 98	≥% 98

antibacterial efficacy of textile fabrics. In accordance with the AATCC 147 standard, pre-prepared bacterial concentrations are introduced into the medium, followed by the placement of fabric samples with a diameter of 25 mm. Following a 24-hour incubation of the sample fabrics at 37 °C, the efficacy of the sample fabric is assessed in millimetres by measuring the diameter of the inhibitory zone surrounding the fabric. The agar diffusion method, a quantitative approach, assesses the antibacterial activity of treated fabrics, allowing for evaluations of their effectiveness [22].

*Escherichia coli (*ATCC 35150) and *Staphylococcus aureus* (ATCC 25923) are cultured in petri dishes, after which nonwoven textiles, each measuring 25 mm in diameter, are positioned in containers. The effectiveness of the antibacterial activity is measured in millimetres by looking at the size of the clear area around the fabric after the nonwoven materials were kept at 37 °C for 24 hours.

Bacterial filtration efficiency assessment of a mask

Bacterial filtration efficiency (BFE) quantifies a material's resistance to bacterial infiltration. The bacterial filtering efficiency test is conducted utilising the GT-RAO2 tester. An aerosol comprising microorganisms of a specific size (e.g., *Staphylococcus aureus*) is discharged towards the mask. The dimensions of the bacterial particles typically measure approximately 3 μm. The test is typically conducted at an airflow rate of 28.3 l/min. A segment of the aerosol is transmitted via the mask, and the mask's filtering efficacy is assessed. The results are expressed as a % efficiency, indicating the fabric's capacity to withstand bacterial penetration. Elevated values in this assessment signify enhanced barrier efficacy. The ASTM F2101 standard test protocol defines it as the proportion of particles filtered out by the mask. This testing method is specifically formulated to assess the bacterial filtration efficiency of medical face masks, utilising *Staphylococcus aureus* as the challenge organism. The utilisation of *S. aureus* is predicated on its clinical significance as a predominant cause of nosocomial infections. The highest filtration efficiency ascertained by this technology is 99.9% [23].

Mask breathability assessment

The breathability assessment is conducted in accordance with MIL-M-36954 C. This assessment evaluates a face mask's resistance to airflow. A regulated airflow is sent through the mask, and the pressure differential (ΔP) is monitored before and after the passage. The pressure differential is divided by the sample's surface area (in cm^2). Reduced breathing resistance signifies an enhanced comfort level for the user.

The classification of surgical masks is presented in table 3 in accordance with ASTM F 2101 and MIL-M-36954 C standards.

RESULTS AND DISCUSSION

The measurement conducted using the HPLC instrument indicates that the concentration of oleuropein in 1 gram of extract is 106.9 mg/g. The olive leaf utilised in the experiment has 10.6% oleuropein. The chromatogram of the sample is presented in figure 5. The graph verifies that the apex at the 66th minute corresponds to oleuropein.

Figure 6 presents the widths of zones created in the fabric as a consequence of the test conducted in

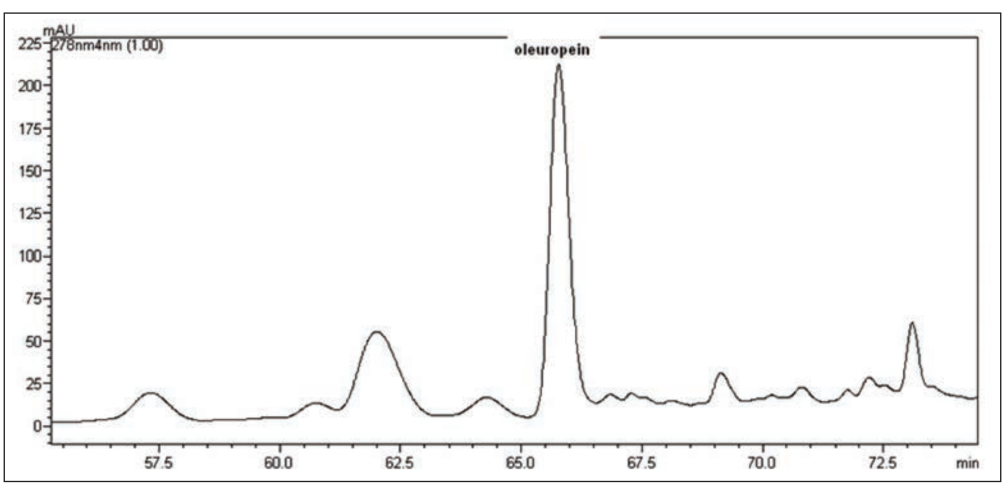

Fig. 5. The chromatogram produced by the HPLC apparatus

a *b*

Fig. 6. The zone diameter produced by the mask containing 20% extract on: *a* – *S. aureus* bacteria; *b* – *E. coli* bacteria

accordance with the AATCC 147 diffusion agar method. The zone diameter for *S. aureus* bacteria is illustrated in figure 6, *a*, while the zone diameter for *E. coli* bacteria is depicted in figure 6, *b*. A 47 mm zone of inhibition is observed against *S. aureus*, while a 40 mm zone is noted against *E. coli*.

The findings indicate that olive tree leaves in the Mediterranean region contain approximately 10.6% oleuropein. The absorption of the olive leaf extract into the three-layer mask fabric and its adherence to the fabric are effectively achieved utilising the "soaking-drying" approach, which is both straightforward and cost-effective.

The study also found that olive leaf extract is particularly effective against *S. aureus* and *E. coli* bacteria. The study's tests indicate that fabric infused with olive leaf extract exhibits superior efficacy against *S. aureus* bacteria, with a measured inhibition zone diameter of 47 mm. The inhibition effect against *E. coli* bacteria is found to be inferior to that against S. aureus bacteria, with a measured zone diameter of 40 mm. This effect is believed to be associated with the cell wall of *E. coli* bacteria.

These results correspond with the literature. A study indicates that oleuropein derived from olive leaves exhibits significant efficacy against *S. aureus* bacteria, with an inhibitory diameter of 30.18 mm [24]. A different investigation revealed that a combination of phenolic compounds from olive leaves exhibited superior antibacterial action compared to individual phenolic compounds examined in isolation [25]. Consequently, they exhibited the antibacterial properties of phenolic compounds found in olive leaves.

The bacterial efficiency test is performed on masks with and without oleuropein added, following the ASTM F2101 standard, using ten repetitions to find the average results. Table 4 presents the mean results. Upon examination of the values, it is observed that the average bacterial filtration effectiveness of masks without an oleuropein additive is 96.7%; however, this number increases to 98.5% in masks with an oleuropein additive. The oleuropein addition enhanced the bacterial filtering performance of the masks by 2.2%. Upon examination of the breathability values of the masks, it is evident that the addition of oleuropein diminishes the breathability of the mask. This phenomenon is believed to arise from the

Table 4

BACTERIAL EFFICIENCY AND BREATHABILITY RESULTS

Type of mask	Bacterial efficiency average (%)	Breathability average (mm H_2O)
Non-additive mask	96.7	3.7
Mask with oleuropein	98.5	4.8

oleuropein additive closing the pores between the fibres, which aligns with existing literature.

CONCLUSION

The HPLC test conducted on olive leaves from olive trees in Antalya province, Türkiye, revealed a high oleuropein concentration of approximately 10.6%. In line with the literature, oleuropein is identified as the predominant phenolic compound in olive leaves.

The extract derived from olive leaves has been applied to the fabric by the "soak-hold-dry" technique and has effectively been integrated into the fabric. The employed procedure is remarkably straightforward and cost-effective. The olive leaves utilised in the study are wastes generated post-harvest. Thus, the waste olive leaves not only have been converted into a high-value product, but also the creation of environmental waste has been prevented.

Antibacterial effectiveness assessments have been conducted on oleuropein additive textiles against *S. aureus* and *E. coli* bacteria in accordance with the AATCC 147 standard. The test findings indicated that the textiles exhibited a zone diameter of 40 mm against *E. coli* bacteria and a zone diameter of 47 mm against *S. aureus* bacteria. It is determined that fabrics treated with oleuropein exhibit better effectiveness against *S. aureus* bacteria.

E. coli bacteria are widely recognised in the field of medicine. This bacterium is a type of gram-negative bacterium that proliferates at body temperature, leading to various illnesses and exhibiting infectious properties. *S. aureus* is a gram-positive bacterium that induces several illnesses in humans. These bacteria are prevalent because of their resilience to fluctuating climatic conditions and are predominantly located in wounds of the nose, throat, and skin. Direct contact with air and surfaces can spread these bacteria. Using oleuropein additives in medical textiles will reduce the spread of these bacteria and help prevent diseases caused by them. The findings have indicated that the oleuropein addition enhanced the bacterial efficiency value of masks by 2%. According to ASTM F2101 standards, a non-additive mask has exhibited an average bacterial effectiveness of 96.7%, but the mask including the oleuropein additive has an average bacterial efficiency of 98.5%.

Nevertheless, according to the MIL-M-36954 C standard, the breathability test conducted on the oleuropein additive masks has demonstrated an increase from 3.7 mmH_2O to 4.8 mmH_2O. This result shows a reduction in the mask's breathability. This situation has arisen because the contribution of oleuropein has blocked the gaps between the fibres. Thus, the air permeability of the fabric structure made of fibres has decreased. Nonetheless, the value attained falls within acceptable parameters. ASTM standards categorise masks into three levels: Level 1 – Low barrier protection, Level 2 – Moderate barrier protection, and Level 3 – Maximum barrier protection. Upon examining the data from this study and comparing it with ASTM requirements, we can see that the values of the 'oleuropein additive masks' fall within the Level 2 Barrier classification. It is generally advised to utilise Level 1 Barrier masks for daily protection at a specified distance and in situations with a low risk of bacterial contamination, whereas Level 2 Barrier masks are indicated for scenarios with a high risk of contamination. The result indicates that oleuropein additive masks are suitable for daily use or surgical procedures with a heightened risk of contamination.

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Research on the virtual simulation of the drape of cotton-linen blended fabrics of high bending rigidity

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ABSTRACT – REZUMAT

Research on the virtual simulation of the drape of cotton-linen blended fabrics of high bending rigidity

A major challenge in virtual 3D garment prototyping is still the lack of precise and reliable simulation of the drape of textile materials. Accurate simulation of the fabric drape depends on the CAD 3D programme used, the physical and low-stress mechanical properties of the fabrics and the possibility of varying the simulation parameters, like the density of the 3D fabric polygon mesh, which is particularly important for high-bending-rigidity fabrics. Hence, in this study, the effect of the polygon mesh density on the virtual drape of heavy cotton-linen fabrics with high rigidity, suitable for spring outwear garment, was investigated. Four fabrics were developed with identical yarns and fabric count and differentiated by fabric weave. The virtual drape simulations of the fabrics were performed using the OptiTex software with variable polygon mesh density (0.3–0.9) and were compared with the real fabric drape assessed by the Cusick Drape Tester. In addition, the draping of two virtual 3D garments was analysed to identify differences due to variable polygon mesh density. Largely different physical and low-stress mechanical properties of the fabrics, depending on weave, resulted in different drape behaviour, with plain and satin fabrics displaying the highest (0.91) and lowest (0.86) drape coefficient, respectively. Analysis of the drape coefficients of both real and virtually simulated fabrics suggests that more reliable and realistic simulations of high rigidity fabrics can be achieved with low polygon mesh density (0.7 and 0.9). The density of the 3D fabric polygon mesh slightly influences garment drape simulation and appearance. Specifically, for the skirt, orthogonal projections reveal fold displacement and variations in fold shape and depth correlated with polygon mesh density. These results can help garment developers to carry out realistic simulations of high-rigidity fabrics.

Keywords: *cotton-linen blended fabrics, fabric weave, fabric real drape, virtual drape simulation, polygon mesh density*

Cercetare privind simularea virtuală a drapajului țesăturilor din amestec de bumbac și in cu rigiditate ridicată la îndoire

O provocare majoră în prototiparea virtuală 3D a articolelor de îmbrăcăminte rămâne în continuare lipsa unei simulări precise și fiabile a drapajului materialelor textile. Simularea precisă a drapajului țesăturii depinde de programul CAD 3D utilizat, de proprietățile fizice și mecanice ale țesăturilor cu solicitare redusă și de posibilitatea de a varia parametrii de simulare, cum ar fi densitatea rețelei poligonale 3D a țesăturii, care este deosebit de importantă pentru țesăturile cu rigiditate ridicată la îndoire. Prin urmare, în acest studiu a fost investigat efectul densității rețelei poligonale asupra drapajului virtual al țesăturilor din bumbac-in cu masă mare și rigiditate ridicată, potrivite pentru îmbrăcămintea de primăvară. Au fost dezvoltate patru țesături cu fire și densitate identice, care se diferențiază prin legătura țesăturii. Simulările drapajului virtual al țesăturilor au fost efectuate utilizând software-ul OptiTex cu densitate variabilă a rețelei poligonale (0,3–0,9) și au fost comparate cu drapajul real al țesăturii evaluat cu Cusick Drape Tester. În plus, a fost analizat drapajul a două articole de îmbrăcăminte virtuale 3D pentru a identifica diferențele datorate densității variabile a rețelei poligonale. Proprietățile fizice și mecanice foarte diferite ale țesăturilor, care depind de legătura țesăturii, au dus la un comportament diferit al drapajului, țesăturile cu legătură pânză și cele cu legătură atlaz prezentând coeficientul de drapaj cel mai ridicat (0,91) și, respectiv, cel mai scăzut (0,86). Analiza coeficienților de drapaj ai țesăturilor reale și simulate virtual sugerează că se pot obține simulări mai fiabile și mai realiste ale țesăturilor cu rigiditate ridicată cu o densitate redusă a rețelei poligonale (0,7 și 0,9). Densitatea rețelei poligonale 3D a țesăturii influențează ușor simularea drapajului și aspectul articolului vestimentar. Mai precis, în cazul fustei, proiecțiile ortogonale relevă deplasarea pliurilor și variațiile formei și adâncimii pliurilor corelate cu densitatea rețelei poligonale. Aceste rezultate pot ajuta dezvoltatorii de articole vestimentare să realizeze simulări realiste ale țesăturilor cu rigiditate ridicată.

Cuvinte-cheie*: țesături din amestec de bumbac și in, legătură pânză, drapaj real al țesăturii, simulare virtuală a drapajului, densitatea rețelei poligonale*

INTRODUCTION

In the current context of the textile sector, innovative and sustainable textiles are expected to enter the market, and their digitalisation is necessary for the purpose of garment development, pursuing minimal resource use by means of simulations as an alternative to the production of multiple prototypes.

With around 26 million tonnes, cotton is the second most important fibre in terms of production volume and had a market share of around 24 percent of global fibre production in 2020, while other plant-based fibres, including linen and hemp, had a market share of around 6 percent [1]. As the most up-and-coming natural fibres, linen and hemp have a growing potential for use in various products [2]. The global market for linen fabrics is expected to reach USD 3,125.4 million by 2030, and the compound annual growth rate is expected to exceed 6.2% [3]. Linen is an excellent, environmentally friendly fibre obtained from the inside of the woody stem of the flax plant. The fibre is spun on a long-fibre spinning system [4,5]. It is very absorbent, and linen garments are valued for their exceptional coolness and freshness in hot weather. Linen has several advantages over cotton: it is stronger and conducts heat better than cotton, it is less elastic and stiffer than cotton and creases easily [5]. Linen fabrics are available in various qualities, from ultra-light fabrics to heavy linen canvases. They are used for a wide range of products, from men's and women's clothing to towels, napkins, bed linen, etc. Compared to synthetic fabrics, they do not cause an increase in reactive oxygen species and oxidative stress in the human organism [6] and have a positive effect on the human body in terms of their comfort properties [7, 8, 9]. By blending linen with other compatible natural and man-made fibres, different structural and functional properties can be achieved. Fabrics made of 100% linen and their blends with cotton and viscose have been studied for their physical, mechanical and comfort properties [4]. Okur [1] found that blending linen and hemp with cotton increases the air permeability, water absorption and drying speed.

Based on the blending potential of natural fibres such as linen and hemp, research has increasingly focused on how fabric construction, particularly weave structure, affects the physical and mechanical properties of these textiles. Begum and Milašius [10] have provided an overview of the effects of weave structure on fabric properties, including drapability. Todihi et al. [11] analysed the influence of weave structure on the properties of bending rigidity of fabrics. Matusiak [12] investigated the drapability of twelve cotton fabrics with different structures. Among the examined fabrics, the twill weaves 3/1 S and 2/2 S had the highest drape coefficient, while the rep weave 2/2 (2) had the lowest. Süle [13] noticed an increase in the drape coefficient with increasing weft density and weft yarn thickness, and no influence of warp tension on the drape coefficient.

The shape and aesthetic appearance of garments are influenced by the specific properties of textile materials, especially the bending and shear rigidity and drapability of textiles [14–17]. Numerous studies investigated the relationship between various physical or mechanical properties of the fabric and its ability to drape and highlighted the most important ones in predicting the drape coefficient [18–25], among which fabric stiffness, showing that very stiff fabrics have a high drape coefficient.

For this reason, studies looking at the relationship between mechanical properties and drapeability and garments' shape and appearance in real and virtual environments were conducted for decades. Targeting improved accuracy of virtual drape simulations, the effect of low-stress mechanical properties measured with KES or the FAST measurement system on the drape of the fabric has been investigated in many studies [26–29]. A realistic 3D clothing simulation requires dedicated software programmes, but proprietary algorithms hinder the analysis. In the study by Schiller et al. [30], the VStitcher software was used to evaluate the fabric parameters using drape tests and drape coefficient (DC) calculations. The analysed fabrics had DC values between 0.1 and 0.7. The bending rigidity had the greatest influence on the DC, while the thickness, elongation and shear rigidity had only a minor influence on the DC. In the study by Ashmawi et al. [31], three different fabrics, cotton, polyester and cotton-polyester, were used for virtual 3D simulations of garments using CLO3D software and found that this software is not suitable for simulating garments with optimal simulation of fabric draping. Miguel et al. [32] examined how fabric type, weave and thickness affect the drape behaviour of clothing by comparing single-layer and double-layer fabrics of the same weight in a jacket prototype. Their experimental tests and virtual simulations using Marvellous Designer 8 revealed notable differences in drape and aesthetics, with the double-layer fabric showing less fall but a more harmonious drape than the single-layer fabric. Also, Rudolf et al. [33] studied the effects of fabric properties (such as extension, bending, shear rigidity, and thickness) and simulation parameters (including resolution, solver settings, and soft bending) on fabric draping and the shape and fit of the virtual garments. They recommended using different simulation parameters for soft and flexible fabrics as opposed to rigid fabrics to achieve more realistic drape simulations. The optimal simulation parameters using the OptiTex 3D software, depending on the measured low-stress mechanical properties using the measuring systems FAST and KES, were also investigated by Petrak et al. [34] for nine fabrics (polyester, wool, polyester and wool blends with cotton, viscose, and elastane). They found an optimal polygon size of 0.4 cm for fabrics with a drape coefficient ranging between 0.20 and 0.35, a size of 0.6 cm for fabrics with a drape coefficient between 0.35 and 0.50 and a size of 0.8 cm in the case of a drape coefficient above 0.5. The recent developments of systems for the digitalisation of textiles, based on artificial intelligence, are now opening new possibilities for the virtual 3D prototyping of garments [35–37].

Today, the fashion and clothing industry is increasingly striving to use sustainable and renewable textile materials and to digitise the entire production process. In this context, virtual 3D simulation of garments will continue to play an important role, significantly supporting the development, presentation and sale of garments on the market. Therefore, there is a need for knowledge about the integration of a large range of textiles in a virtual environment with the aim of simulating the draping of virtual 3D garments as realistically as possible.

Hence, this study aims to complement existing research and examine heavy cotton-linen blend fabrics with high bending rigidity, barely considered in other studies. The focus is on the influence of the fabric weave and the size of the triangles of the 3D fabric polygon mesh on the virtual fabric drape and garment simulations using OptiTex 3D software. It hypothesises that for high-bending-rigidity fabrics, more reliable and realistic simulations can be achieved with a lower polygon mesh density.

EXPERIMENTAL

Materials

For this study, four fabrics (FB1 – FB4) were developed on a Dornier industrial rapier weaving loom 1.6 m width differentiated by four distinctive weaves and having identical fabric count and yarn composition, i.e. 150 tex linen yarns and 40 tex cotton yarns in weft and warp direction, respectively. The types of weaves (i.e. plain 1/1, twill 3/1, reinforced twill 1/1 2/2, satin 4/1) were chosen targeting large differences in fabric properties, bending stiffness in particular.

The physical properties of the four fabrics were measured as described in section 2.2.1 and are listed in table 1. The thickness of the fabrics varied roughly between 1.1 mm (plain fabric FB1) and 1.4 mm (satin fabric FB4), and their weight between 339 $g \cdot m^{-2}$ (FB4) and 355 $g \cdot m^{-2}$ (FB1), respectively.

Methodology

The fabrics were conditioned for at least 24 hours according to the standard ISO 139:2005 [38] prior to their physical, low-stress mechanical properties and drapeability being assessed, and the simulations of the garment and fabrics' drape were executed.

Physical properties

The fabric count in warp and weft direction was determined according to the standard ISO 7211/2:1984 [39]. The fabric thickness was measured with a thickness gauge according to the standard ISO 5084:1996 [40] and the fabric weight according to ISO 3801:1977 [41].

Low-stress mechanical properties

The low-stress mechanical properties of the fabrics, including extensibility (E5, E20, E100), shearing rigidity (G), bending rigidity (B) and surface thickness (ST) were measured using a FAST measuring system [42]. The measured mechanical properties of the fabrics were subsequently converted into the units of the OptiTex 3D V11 software [43] and used for the simulation of fabrics and garments' drape.

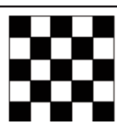
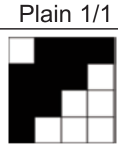
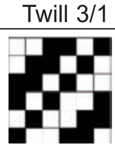
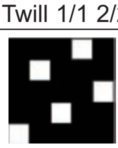
Fabric drape

A Cusick Drape Tester (CDT) (James H. Heal & Co. Ltd., Halifax, England) was used to determine the real drape coefficients of the fabrics using the Drape Analyser software. The pedestal of the Cusick Drape Tester, with a diameter of 18 cm, and the fabric sample with a diameter of 30 cm were used. The orthogonal projections of fabric drapes were taken with a digital camera, and the drape coefficients (DC) were calculated.

To determine virtual fabric drape, a 3D pedestal model with a diameter of 18 cm was imported into the

Table 1

THE PHYSICAL PROPERTIES OF THE FABRICS (FB1-FB4), DEVELOPED WITH IDENTICAL YARNS AND FABRIC COUNT AND DIFFERENTIATED BY FABRIC WEAVE

Fabric code	Weave type	Yarn linear density (tex)		Fabric count (thread/cm)		Fabric thickness (mm)	Fabric weight ($g \cdot m^{-2}$)
		warp	weft	warp	weft		
FB1	 Plain 1/1	150	40	18	10	1.11 ± 0.01	354.92 ± 2.80
FB2	 Twill 3/1	150	40	18	10	1.42 ± 0.01	340.31 ± 2.62
FB3	 Reinforced Twill 1/1 2/2	150	40	18	10	1.39 ± 0.02	348.77 ± 3.22
FB4	 Satin 4/1	150	40	18	10	1.44 ± 0.01	339.96 ± 1.70

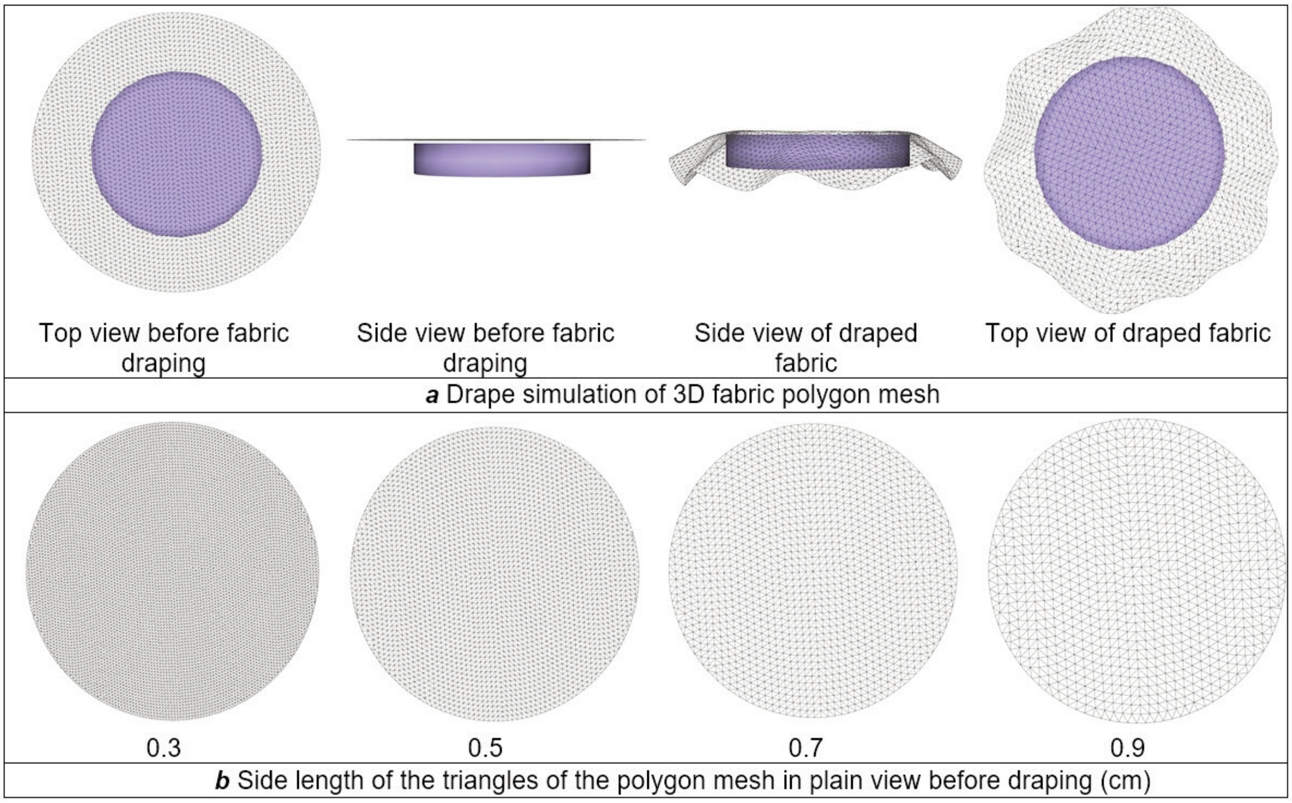


Fig. 1. Fabric drape simulation showing: *a* – fabric top and side view before and after draping; *b* – visualisation of various side lengths (0.3–0.9) of the triangles of the polygon mesh, in the OptiTex 3D software

OptiTex 3D software. Drape simulations of the 30 cm diameter 3D fabric pattern piece were performed using the default simulation parameters (i.e. world, time and stitch parameters) and by varying the density of the 3D fabric polygon mesh.

For the virtual draping, the measured low-stress mechanical properties of the real fabrics were used, i.e. extensibility (E100), bending rigidity (B), shear rigidity (G), surface thickness (ST) and weight (W) were used. The fabric simulations were performed with different densities of the 3D fabric polygon mesh (0.3, 0.5, 0.7, 0.9), corresponding to a side length of the triangles of 0.3 cm, 0.5 cm, 0.7 cm and 0.9 cm, respectively, as shown in figure 1. The position of the virtual 3D fabric pattern piece was kept the same in all simulations.

After simulating each fabric drape, its orthogonal projection was recorded, figure 2, *a*, to compare it with the orthogonal projection of the CDT and to compare the drape coefficients between real fabrics and simulated fabrics.

The orthogonal projections of the draped fabrics were extracted using a CorelDraw software programme [44], and they were imported into the ArchiCAD programme [45], where the surface areas (mm^2) were measured using the Fill/ Dimension tool,

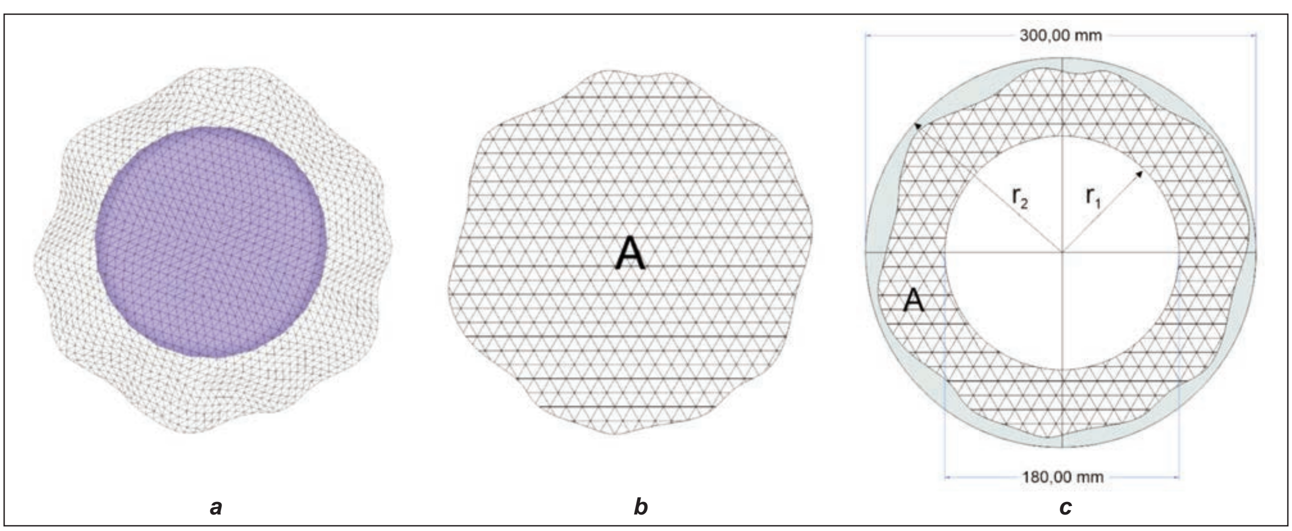


Fig. 2. Procedure for calculating the drape coefficients for virtually draped fabrics: *a* – fabric drape simulation; *b* – surface area of the draped fabric; *c* – parameters for the calculation of the drape coefficient

figure 2, *b*. The drape coefficients (DC) were calculated using equation 1 [46]:

$$DC = \frac{A - \pi r_1^2}{\pi(r_2^2 - r_1^2)} \quad (1)$$

where A (mm^2) is the surface area of the orthogonal projection of the draped fabric, r_1 (mm) – the radius of the pedestal, and r_2 (mm) – the radius of the undeformed fabric sample before draping, figure 2, *c*. The higher the value of DC, the lower the drapability of the fabric [12].

Garments drape

A standard 3D woman's body model available in the library of the OptiTex 3D V11 software was used to carry out the drape simulations of the clothing set consisting of a jacket and an A-line skirt in accordance with the fabrics developed. Drape simulations were performed using the default simulation parameters by varying the density of the 3D fabric polygon mesh (0.3, 0.5, 0.7, 0.9), corresponding to a side length of the triangles of 0.3 cm, 0.5 cm, 0.7 cm and 0.9 cm, respectively.

Measured low-stress mechanical properties of the real fabrics, i.e. extensibility (E100), bending rigidity (B), shear rigidity (G), surface thickness (ST), and weight (W) were used to obtain the garments' drape simulations (figure 3). In the drape simulations, the position of the virtual 3D pattern pieces of garments around the 3D body model was the same in all simulations.

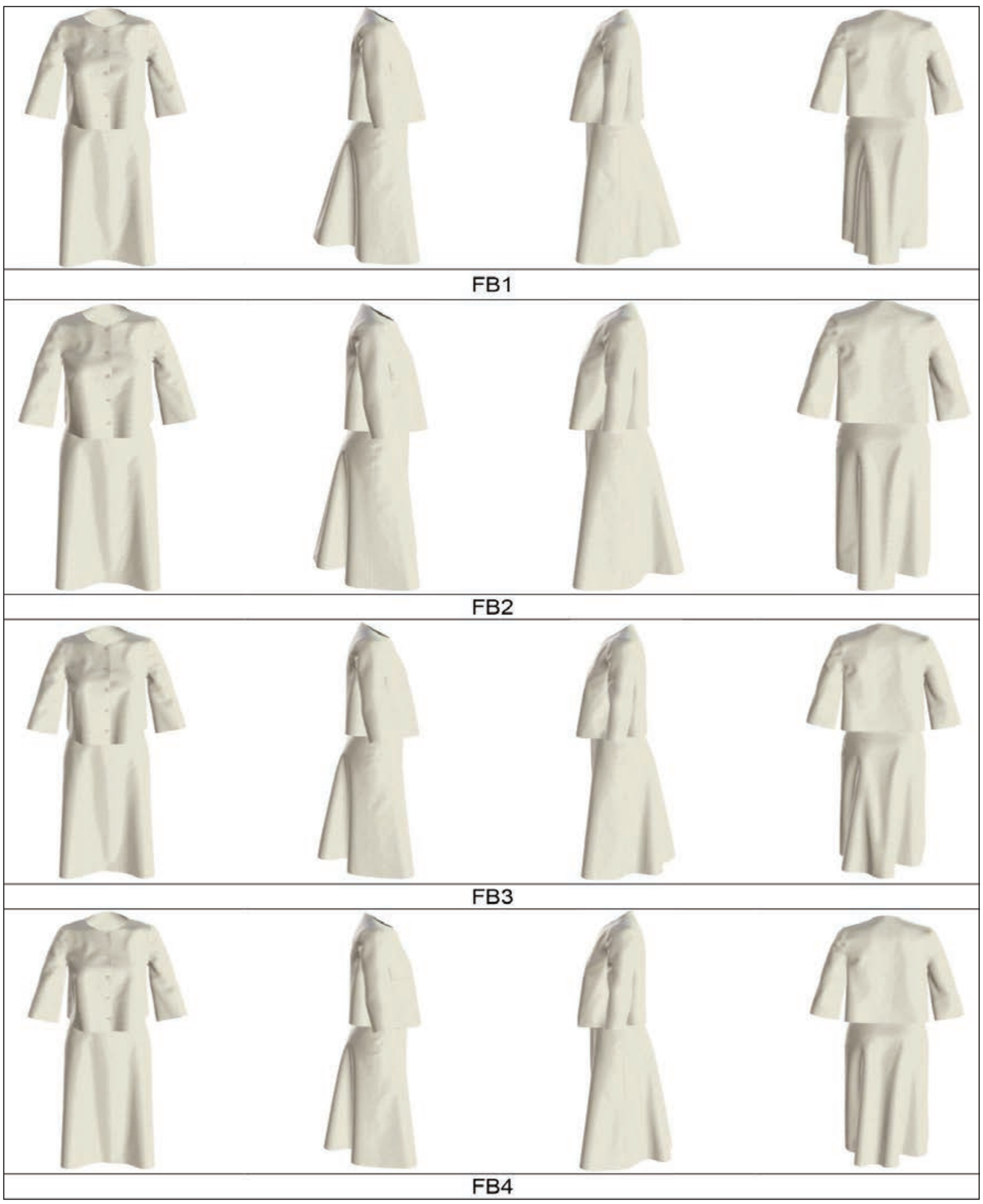


Fig. 3. Simulations of a virtually draped garment, for fabrics FB1–FB4 and a polygon mesh density of 0.9

The simulation of a woman's dress with a 3D fabric polygon mesh density of 0.3 could not be performed; the simulation failed. Therefore, only simulations with densities of 0.5–0.9 were carried out.

After the simulation, the bottom views of both the jacket and skirt were separately recorded (figure 4, *a*) to compare the areas between the 3D fabric polygon mesh densities. The bottom views of the draped jacket without sleeves and skirt were extracted using the CorelDraw programme (figure 4, *b*). They were imported into the ArchiCAD programme, and their surface areas (m^2) were measured using the Fill/ Dimension tool (figure 4, *c*).

Comparison of the real and simulated fabrics' drape coefficients and surface areas of draped garments

Comparisons between the orthogonal projections of the real and virtual fabrics' drapes based on the Cusick method and between the surface areas of 3D virtually draped garments were performed to investigate the effect of the 3D fabric polygon mesh densities on the drape simulations of the developed fabrics. For this purpose, the absolute (Δ) and relative (%) differences between the drape coefficients of fabric FB1 and the other three fabrics (FBX) were calculated, as well as the drape coefficient of the real (DCCDT) and virtually simulated fabrics for various polygon mesh densities (DC0.3, DC0.5, DC0.7, DC0.9). The surface areas of the orthogonal projections of the jacket without sleeves and the skirt were compared between 3D fabric polygon mesh densities.

RESULTS AND DISCUSSION

In this section, the low-stress mechanical properties of the four cotton-linen blended fabrics measured with the measuring system FAST are first analysed, and their correlations with the measured drape coefficients are discussed. Subsequently, the real and the virtually simulated draped fabrics are compared, whereby the importance of the polygon mesh density becomes clear. The virtually simulated draped garments are compared depending on the polygon mesh density to determine their effect on the draping of garments.

Analysis of the low-stress mechanical properties and drape coefficients

The measured low-stress mechanical properties of the fabrics using the FAST measuring system are displayed in table 2. The extensibility E5, E20, E100 (%) corresponds to a fabric load of 4.91 $N \cdot m^{-1}$, 19.62 $N \cdot m^{-1}$ and 98.07 $N \cdot m^{-1}$ respectively. They were assessed in warp (i.e. E100-1) and weft (E100-2) directions, similar to bending rigidity (B-1) and (B-2), respectively.

Among the four fabrics tested, plain fabric FB1 had the highest bending rigidity (B-1 = 201.42 $\mu N \cdot m$, B-2 = 285.55 $\mu N \cdot m$), shear rigidity (G = 738.00 $N \cdot m^{-1}$) and weight (354.92 $g \cdot m^{-2}$) and the lowest extensibility (E100-1 = 0.87%, E100-2 = 0.20%) and surface thickness (ST=0.189 mm). It is followed by the reinforced twill fabric FB3 with a lower bending rigidity

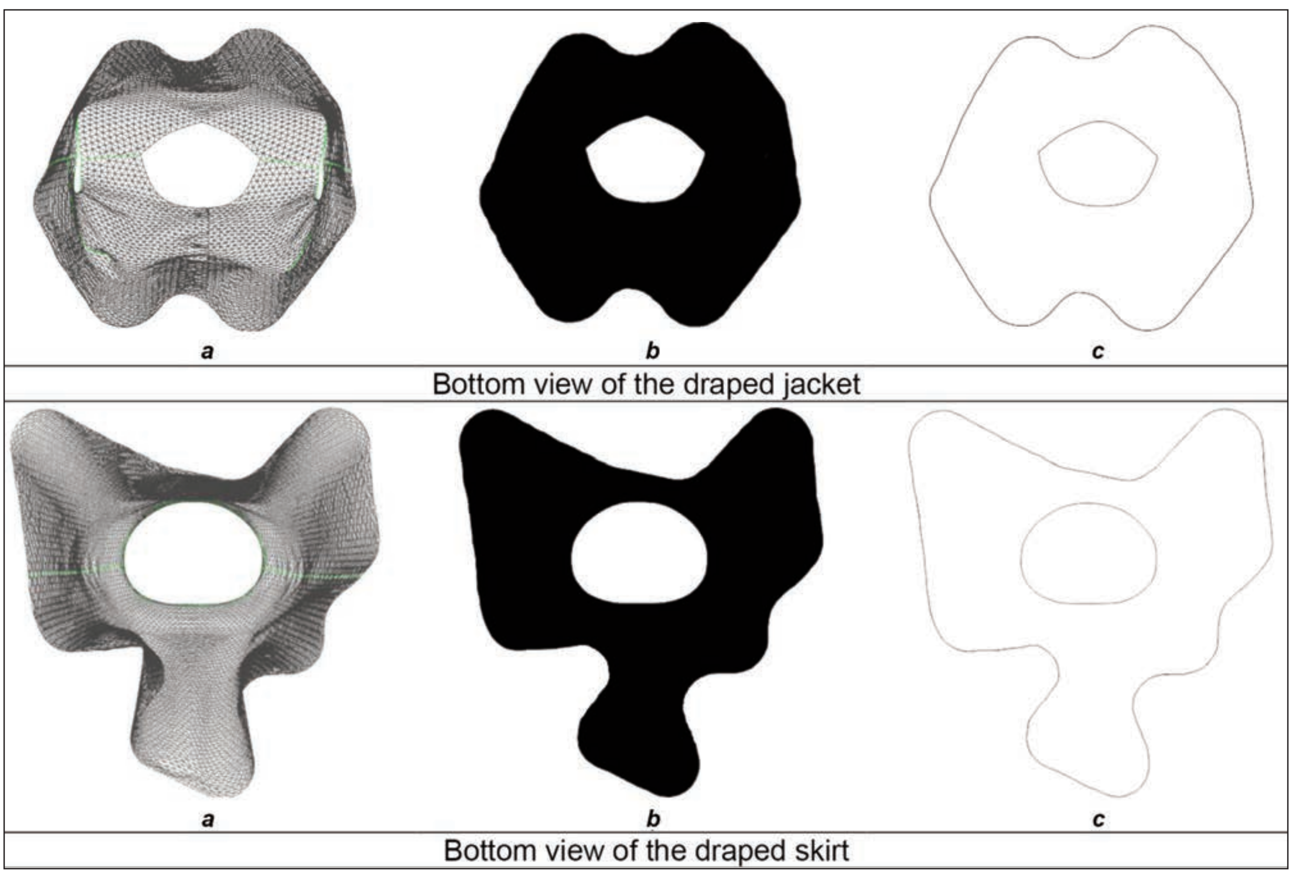


Fig. 4. Procedure for calculating the surface area of the garments (fabric FB4, polygon mesh density 0.9): *a* – OptiTex bottom view; *b* – CorelDraw extracted orthogonal projection; *c* – ArchiCAD surface area

(B-1 = 154.37 μN·m, B-2 = 153.30 μN·m), shear rigidity (G = 295.20 $N \cdot m^{-1}$) and weight (348.77 $g \cdot m^{-2}$), a higher extensibility (E100-1 = 1.53%, E100-2 = 0.33%) and the highest surface thickness (ST = 0.278 mm). Among the two twill fabrics FB2 and FB3 investigated, fabric FB2 had the lowest bending rigidity (B-1 = 141.96 μN·m, B-2 = 173.36 μN·m), shear rigidity (G = 157.02 $N \cdot m^{-1}$), weight (340.31 $g \cdot m^{-2}$), extensibility (E100-1 = 1.47%, E100-2 = 0.27%) and surface thickness (ST = 0.217 mm). Satin fabric FB4 has the lowest bending rigidity (B-1 = 111.29 μN·m, B-2 = 134.16 μN·m), shear rigidity (G = 60.49 $N \cdot m^{-1}$) and weight (339.96 $g \cdot m^{-2}$), and the highest extensibility (E100-1 = 1.60%, E100-2 = 0.73%) among the examined fabrics and its surface thickness (ST = 0.250 mm) is slightly lower than that of the thickest fabric FB3.

As expected, plain weave (FB1) had the highest bending rigidity and satin weave (FB4) the lowest, which is also consistent with the findings of Tohidi et al. [11]. They investigated woven polyester fabrics differentiated by five weaves (i.e. plain, 1/2 twill, 1/3 twill, 1/4 twill and 1/5 twill), and concluded that the increase in float yarns resulted in a strong decrease in bending rigidity regardless of the fabric direction.

The extensibility parameters E5 and E20 were used to calculate the shear rigidity and calculated fabric formability F, but the latter is not needed to simulate draping of textiles with OptiTex 3D software. For all four fabrics, the extensions at loads of 4.91 $N \cdot m^{-1}$ (E5) and 19.62 $N \cdot m^{-1}$ (E20) are extremely low, which is reflected in the high shear rigidity and drape coefficients of all examined fabrics. The extensibility of all fabrics was higher in the warp direction, regardless of the load.

Considering the similar fabric count and yarns used, the results suggest a significant influence of the weave on the physical and low-stress mechanical properties of the four cotton-linen blend fabrics investigated. In particular, a pronounced linear trend of the dependence of the weave on the weight (R^2 = 0.90), the bending rigidity in the warp direction (R^2 = 0.95) and the shear rigidity (R^2 = 0.87) was found, as illustrated in figure 5. On the contrary, this linear dependence is less pronounced in the case of thickness, extensibility and bending rigidity in the weft direction. The results of the drape coefficients of the fabrics (table 2) indicate the plain fabric FB1 as having the highest drape coefficient (0.92), followed closely by FB3 (0.90), FB2 (0.88) and FB4 (0.87).

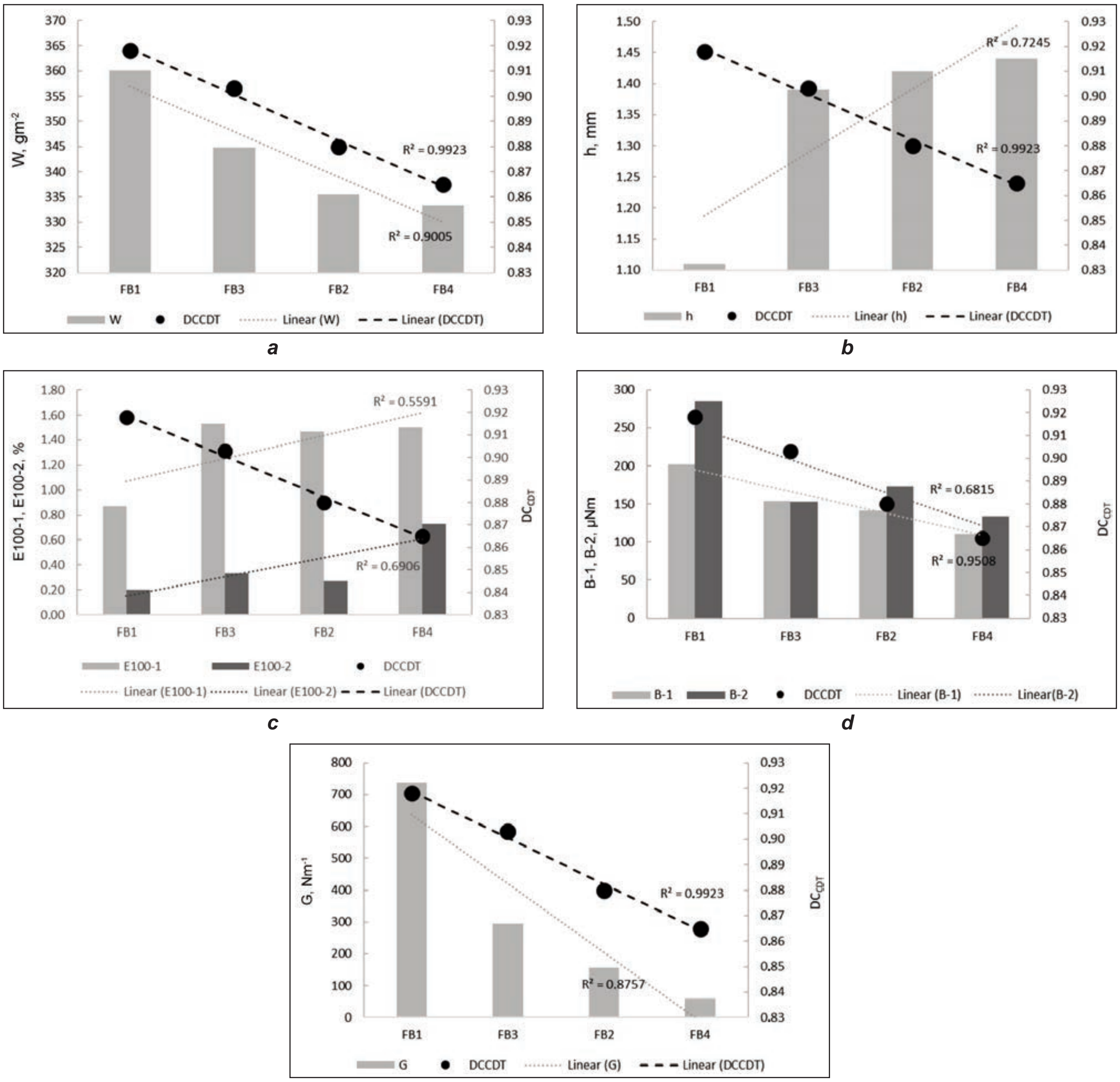
The results of the drape coefficients of the fabrics (table 2) indicate the plain fabric FB1 as having the highest drape coefficient (0.92), followed closely by FB3 (0.90), FB2 (0.88) and FB4 (0.87). In figure 5, we also see a clear linear dependence between the drape coefficient (R^2 = 0.99) and the weave type, the highest for plain weave 1/1 (FB1), followed by twill weave 1/1 2/2 (FB3), twill 3/1 (FB2) and satin 4/1 (FB4). The comparison between the drape coefficient and the weight, thickness, extensibility, bending rigidity and shear rigidity shows a clear trend: the higher the weight, bending rigidity and shear rigidity, and the lower the thickness and extensibility, the higher the drape coefficient of the examined fabrics (figure 5, *a*–*e*). Given the identical yarn and fabric count of the four fabrics, this can only be attributed to the differences in weave, and these differences are especially visible for bending and shear rigidity. These findings are aligned with previous studies [10, 12, 47–49], which investigated the relationship between the fabric weave, mechanical properties and drapability of the fabric. Among the fabrics they examined, Matusiak [12] found that the twill weaves 3/1 S and 2/2 S had the highest drape coefficient and the rep weave 2/2 the lowest for cotton fabrics with the same linear warp density and two different weft densities. Lightweight fabrics usually have lower DC compared to heavy fabrics [47]. In these studies, the weight and

Table 2

LOW-STRESS MECHANICAL PROPERTIES OF FABRICS FB1-FB4, MEASURED BY THE FAST SYSTEM AND DRAPE COEFFICIENTS (DC) MEASURED BY THE CUSICK DRAPE TESTER (CDT)

Fabric code		Mechanical parameters						Drape coefficient (DC_{CDT})
		Extensibility (%)			Bending rigidity B (μN·m)	Shear rigidity G ($N \cdot m^{-1}$)	Surface thickness ST* (mm)	
		E5	E20	E100				
FB1	Warp	0.03	0.13	0.87	201.42	738.00	0.189	0.92
	Weft	0.00	0.03	0.20	285.55			
FB2	Warp	0.20	0.43	1.47	141.96	157.02	0.217	0.88
	Weft	0.00	0.00	0.27	173.36			
FB3	Warp	0.17	0.40	1.53	154.37	295.20	0.278	0.90
	Weft	0.00	0.04	0.33	153.30			
FB4	Warp	0.13	0.40	1.60	111.29	60.49	0.250	0.87
	Weft	0.03	0.30	0.73	134.16			

Note: *Surface thickness ST is calculated as the difference between the fabric thickness at a load of 0.196 $kN \cdot m^{-2}$ and the fabric thickness at a load of 9.807 $kN \cdot m^{-2}$. Fabric thickness is assessed according to ISO 5084:1996, which explains the differences noticeable in table 2 and table 1.



e

Fig. 5. Relationship between the measured drape coefficient (DC_{CDT}) and: *a* – the weight; *b* – thickness; *c* – extensibility in warp (E100-1) and weft direction (E100-2); *d* – bending rigidity in warp (B-1) and weft direction (B-2); *e* – the shear rigidity of the fabrics

thickness of the fabrics were lower than those of the fabrics FB1–FB4; thus, drapability results cannot be directly compared. However, we can observe a similar trend, indicating that fabrics with greater weight and thickness have higher bending and shear rigidity, which translates into lower drapability in both real and virtual environments [33, 34, 48].

The Pearson correlation coefficient (table 3) also shows a very high positive correlation (0.92–0.96) between the drape coefficient of the fabric and its bending rigidity, shear rigidity and weight, meaning the higher the weight, bending and shear rigidity of the fabric, the higher the drape coefficient. On the contrary, we observe a high negative correlation between the drape coefficient and the extensibility of the fabric (–0.78 and –0.79); the lower the extensibility of the fabric, the higher the drape coefficient. A very high correlation (0.90–0.99) was also found between weight, bending and shear rigidity.

These results indicate a strong dependency between the drape coefficient of the fabric and its physical and mechanical properties, weight, bending and shear rigidity in particular, which all reflect the contribution of the weave.

Analysis of real and virtually simulated draped fabrics

Drape simulations of the 3D virtual fabrics were performed using Optitex 3D software by varying the side length of the triangles of the polygon mesh (0.3 cm, 0.5 cm, 0.7 cm, 0.9 cm). The low-stress mechanical properties measured for four fabrics were used for the simulations of the drape. The orthogonal projections of the real and simulated fabrics are shown in

Table 3

CORRELATION BETWEEN THE DRAPE COEFFICIENTS AND PHYSICAL AND LOW-STRESS MECHANICAL PROPERTIES									
		DC_{CDT}	**E100-1**	**E100-2**	**B-1**	**B-2**	**G**	**ST**	**W**
Real drape coefficient	DC_{CDT}	1.00							
Extensibility (at 98.07 $N \cdot m^{-1}$), in warp direction	E100-1	–0.78	1.00						
Extensibility (at 98.07 $N \cdot m^{-1}$), in the weft direction	E100-2	–0.79	0.63	1.00					
Bending rigidity in warp direction	B-1	0.96	–0.92	–0.83	1.00				
Bending rigidity in the weft direction	B-2	0.79	–1.00	–0.68	0.93	1.00			
Shear rigidity	G	0.92	–0.96	–0.68	0.98	0.95	1.00		
Fabric surface thickness	ST	–0.33	0.81	0.49	–0.60	–0.83	–0.61	1.00	
Fabric weight	W	0.95	–0.91	–0.65	0.96	0.90	0.99	–0.51	1.00

table 4, where the shapes of the orthogonal projections of all real draped fabrics show an indistinct number of shallow folds. However, differences can be observed between the drapes of fabrics depending on the weaves, in accordance with their drape coefficients from table 2.

The same applies to orthogonal projections of virtually simulated fabrics, which differ from real fabrics, especially in the case of simulated drapes with a polygon mesh density of 0.3 and 0.5. The folds are more pronounced, and their number appears to be slightly higher. On the contrary, less pronounced and

Table 4

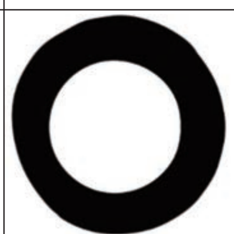
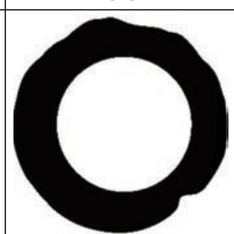
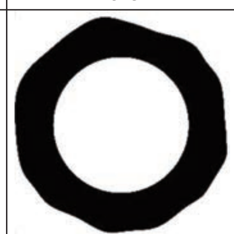
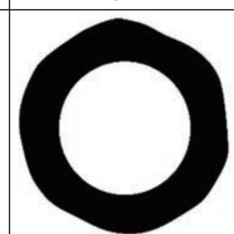
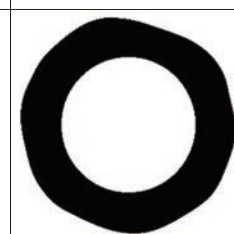
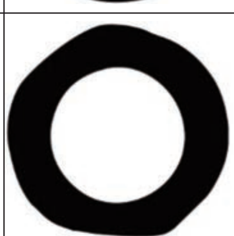
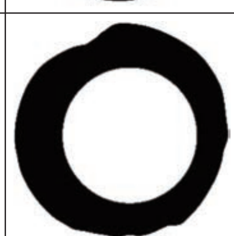
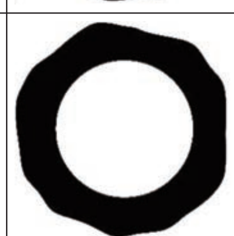
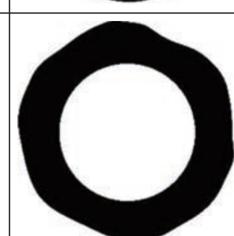
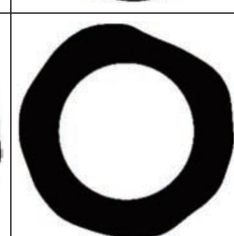
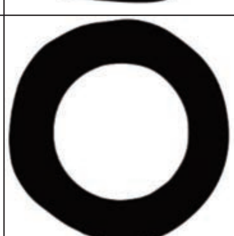
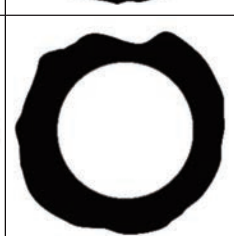
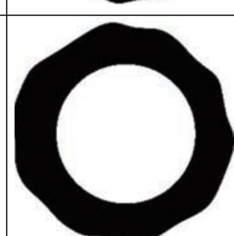
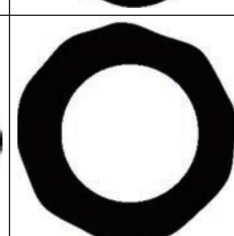
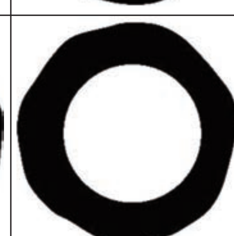
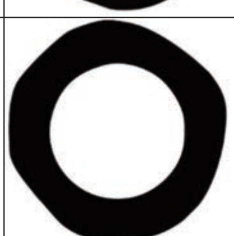
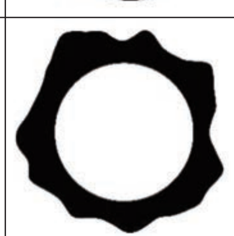
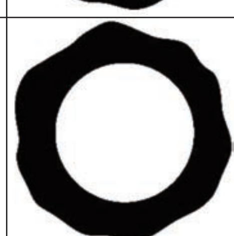
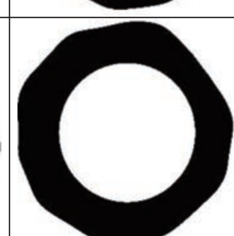
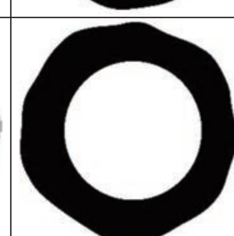
ORTHOGONAL PROJECTIONS OF THE DRAPED FABRICS MEASURED BY CUSICK DRAPE TESTER AND SIMULATED BY OPTITEX 3D, AT FOUR LEVEL DENSITY POLYGON MESH (0.3–0.9)					
Fabric	**Cusick Drape Tester**	**OptiTex 3D / Density of the polygon mesh**			
		0.3	**0.5**	**0.7**	**0.9**
FB1					
FB2					
FB3					
FB4					

Table 5

DRAPE COEFFICIENT FOR REAL (DC_{CDT}) AND VIRTUAL DRAPED FABRICS (DC) AT VARIOUS DENSITIES OF POLYGON MESH (0.3–0.5–0.7–0.9)					
Fabric	**DC_{CDT} Δ $DC_{CDT}(FB1–FB_X)$ Δ $DC_{CDT}(FB1–FB_X)$ (%)**	**OptiTex / Density of the polygon mesh**			
		$DC_{0.3}$ Δ (DC_{CDT}– $DC_{0.3}$) Δ (DC_{CDT}– $DC_{0.3}$) (%)	**$DC_{0.5}$ Δ (DC_{CDT}–$DC_{0.5}$) Δ (DC_{CDT}–$DC_{0.5}$) (%)**	**$DC_{0.7}$ Δ (DC_{CDT}–$DC_{0.7}$) Δ (DC_{CDT}–$DC_{0.7}$) (%)**	**$DC_{0.9}$ Δ (DC_{CDT}–$DC_{0.9}$) Δ (DC_{CDT}–$DC_{0.9}$) (%)**
FB1	0.918	0.834 **0.08** **9.14**	0.827 **0.09** **9.95**	0.860 **0.06** **6.27**	0.860 **0.06** **6.27**
FB3	0.903 **0.02** **1.63**	0.759 **0.14** **15.96**	0.816 **0.09** **9.61**	0.856 **0.05** **5.25**	0.857 **0.05** **5.08**
FB2	0.880 **0.04** **4.14**	0.842 **0.04** **4.33**	0.807 **0.07** **8.32**	0.844 **0.04** **4.08**	0.835 **0.04** **5.10**
FB4	0.865 **0.05** **5.77**	0.603 **0.26** **30.25**	0.784 **0.08** **9.32**	0.840 **0.03** **2.90**	0.836 **0.03** **3.32**

shallower folds are observed at polygon mesh densities of 0.7 and 0.9 for all virtually simulated fabrics, which approach the appearance of the orthogonal projections of the real draped fabrics.

The results of the drape coefficients of real and virtually simulated fabrics are shown in table 5. The results in this table are ordered FB1-FB3-FB2-FB4, starting with the fabric with the highest drape coefficient and ending with the lowest. The absolute (Δ) and relative (%) differences between the drape coefficients for fabric FB1 and the other three fabrics (FBX) were calculated. Similarly, the differences between the drape coefficient of real fabrics (DCCDT) and the drape coefficients of virtually simulated fabrics at different polygon mesh densities (DC0.3, DC0.5, DC0.7, DC0.9) were also calculated, both as absolute (Δ) and relative (%) differences.

As we have already established, the weave of the fabric affects the drape coefficient. This was highest (0.918) for real plain fabric FB1 and lowest (0.865) for fabric FB4 in satin 4/1 weave, and has decreased by 5.77%. The drape coefficient decreased by 4.14% in the case of fabric FB2 in twill 3/1 weave and by 1.63 % for FB3. Though small, these differences in the drape coefficients are visible for the virtually simulated fabrics (table 4).

For all four fabrics, the percentage difference in drape coefficient between the real and the virtually simulated fabric is greatest at a polygon mesh density of 0.3, ranging from 30.25% (FB4) to 4.33% (FB2). In case of a polygon mesh density 0.5, these were smaller, ranging from 8.32% (FB2) to 9.95% (FB1). By further decreasing the density of the polygon mesh to 0.7 and 0.9, the difference between the drape of the real and virtual fabrics decreases for all fabrics, especially for the fabric FB4, and deviates from the real drape coefficient only by 2.90% (polygon mesh 0.7) and by 3.32% (density of the polygon mesh 0.9).

More realistic clothing simulations are usually achieved with a higher density of the polygon mesh [33, 34] of the 3D fabric model (shorter side length of the triangles of the polygon mesh), but this does not seem to apply to rigid textiles. Based on our results, it can be concluded that with a lower density polygon mesh, i.e. a longer side length of the triangles of the polygon mesh of the 3D fabric model, more reliable and realistic simulations can be obtained for rigid fabrics like those investigated in this study.

Analysis of virtually draped garments

The surface areas of the orthogonal projections of the virtually simulated jacket and skirt for various polygon mesh densities (0.5, 0.7, 0.9) are shown in figure 6.

For all fabrics, a similar trend towards a decreasing surface area of the orthogonal projections of the virtually simulated skirt can be observed, depending on the mesh density of the 3D fabric polygons. Specifically, the smallest surface areas for the skirt projections correspond to a mesh density of 0.9, except for fabric FB1. Conversely, the jacket simulations exhibit the largest surface areas of orthogonal projections at the polygon mesh density (0.9), whereas the smallest orthogonal projection areas occur at a polygon mesh density of 0.7.

The anticipated influence of polygon mesh density on the orthogonal projection surface area manifests differently between the skirt and jacket simulations. These discrepancies are likely attributable to the distinct draping conditions inherent to each garment. The skirt drapes freely from the waist and over the hips downward, allowing greater fabric displacement, whereas the jacket conforms more closely to the shoulder blades and arms, restricting drape in these regions and permitting freer fabric fall over the chest and shoulders. Additionally, the skirt pattern encompasses a larger surface area and length as compared

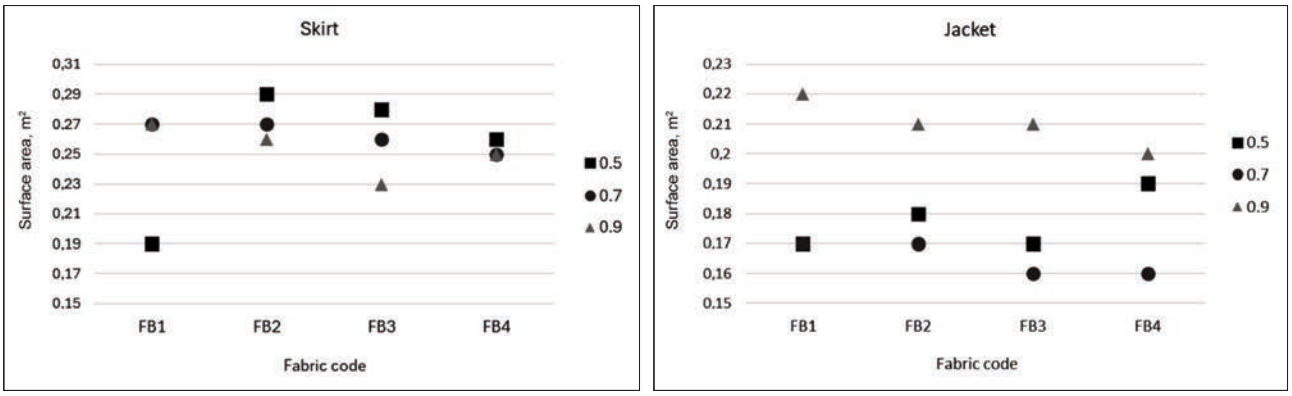


Fig. 6. Surface areas of the orthogonal projections of the virtually simulated jacket and skirt depending on the 3D fabric polygon mesh densities (0.5–0.9)

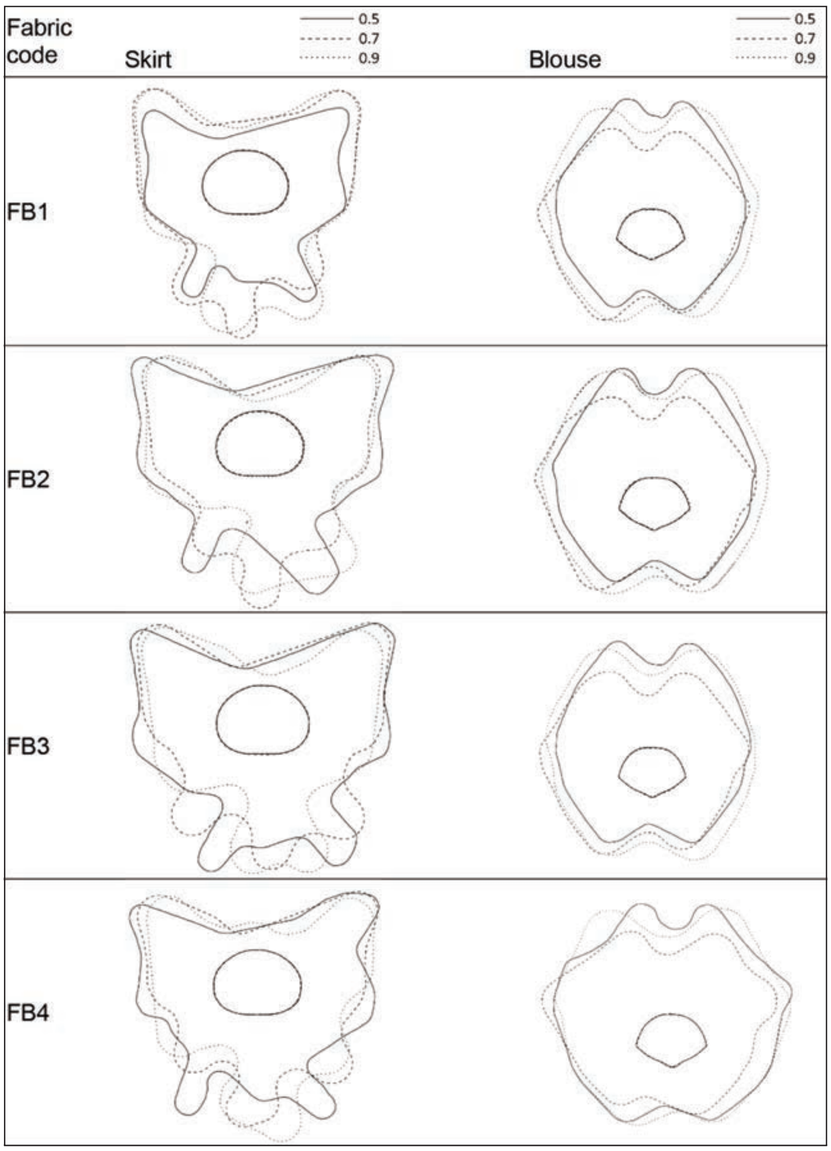


Fig. 7. Comparison between the orthogonal projections of 3D virtually draped garments for researched 3D fabric polygon mesh densities

to the jacket, resulting in greater fabric weight, which may further impact draping behaviour. These observations are further substantiated by figure 7, which shows variations in fabric draping as a function of weave structure and, consequently, the associated physical and mechanical properties, alongside the polygon mesh densities applied in the virtual 3D clothing simulations. In particular, the draping of the skirt shows pronounced changes in fold displacement, shape and depth as a function of polygon mesh density, as shown in the orthogonal projections. In contrast, the draping of the jacket mainly shows variations in fold depth and less pronounced changes in fold geometry.

Based on the results obtained, it can be inferred that the density of the 3D fabric polygon mesh influences the simulation outcomes of garment drape and the resultant visual appearance. Nonetheless, to quantitatively ascertain the precise impact of polygon mesh density on accurate garment drape simulations, further systematic investigations are required. Such studies should encompass a broader range of garment patterns and consider variations in their styles and surface areas to comprehensively validate and extend these preliminary findings.

CONCLUSIONS

For this study, four fabrics were produced from cotton-linen blends, with the same yarns and fabric count but different types of weave. The low-stress mechanical properties of the examined fabrics were measured with the measuring system FAST and imported into the OptiTex 3D V11 software. The virtual simulations of fabric drapes were carried out as a function of the size of the triangles of the polygon mesh of the 3D fabric model. The effect of the fabric weave on the real drape was investigated with the Cusick Drape Tester, and the real drape was compared with the virtual drape simulations. Virtual simulations of the draping of the analysed fabrics were carried out as a function of the polygon mesh densities.

The results clearly showed the effect of the fabric weave on the low-stress mechanical properties and drape of the fabrics. The drape coefficient strongly relates to the physical and mechanical properties of the fabrics, weight, bending and shear rigidity in particular.

The fabric with plain weave encountered the highest drape coefficient, and the satin fabric the lowest. The drape coefficients of real and virtually simulated fabrics show that, in the case of rigid fabrics, more reliable and realistic simulations can be achieved with a lower polygon mesh density. This trend is observed based on a limited number of rigid fabrics and needs to be further validated with other similar fabrics, consisting of different yarns and weaves. Future research should also focus on the simulation of garments with different patterns to clarify the discrepancies found between the different polygon mesh densities needed for a realistic simulation of different types and sizes of garments.

The acquired knowledge on the draping of very rigid natural cotton-linen blended fabrics should help developers to realise realistic simulations necessary for the reliable development of virtual garments.

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Digital lifeboat: Can Fintech development prevent shipwrecks in the textile industry?

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HAN YAN
SHENGLIN MA

ABSTRACT – REZUMAT

Digital lifeboat: Can Fintech development prevent shipwrecks in the textile industry?

The textile industry's lengthy supply chains, narrow profit margins, and substantial working capital pressures render financial risk management a critical determinant of sustainable industry development. Digital finance, through technological innovation, offers textile firms novel risk management tools. Drawing on information asymmetry theory and financing constraint theory, this study examines how digital finance affects textile firms' financial risk and the underlying mechanisms. Using 3,443 firm-year observations from Chinese A-share textile industry listed companies spanning 2014–2023, we employ two-way fixed effects models to identify these relationships. Results show that digital finance development significantly reduces textile firms' financial risk levels. Mechanism tests reveal that digital finance operates through two pathways, namely alleviating information asymmetry and easing financing constraints, with these pathways exhibiting complementary effects. Heterogeneity analysis demonstrates that digital finance's risk-mitigating effects are more pronounced in central and western regions, firms with greater media coverage, non-state-owned enterprises, and large firms. These findings provide theoretical foundations and practical guidance for textile firms to leverage digital finance tools to optimise financing strategies and enhance risk management capabilities, while also offering policy insights for promoting digital transformation and high-quality development in the textile industry.

Keywords: *textile value chain firms, digital finance, financial risk, information asymmetry, financing constraints*

Colacul de salvare digital: poate dezvoltarea Fintech să prevină declinul industriei textile?

Industria textilă, caracterizată prin lanțuri de aprovizionare extinse, marje reduse de profit și presiuni semnificative asupra capitalului de lucru, se confruntă cu provocări financiare care fac din managementul riscului un element esențial pentru dezvoltarea sustenabilă a sectorului. În acest context, finanțarea digitală oferă noi oportunități pentru îmbunătățirea gestionării riscului financiar la nivelul firmelor. Pe baza teoriei asimetriei informaționale și a teoriei constrângerilor de finanțare, acest studiu analizează impactul finanțării digitale asupra riscului financiar al firmelor textile, precum și mecanismele prin care acest efect se produce. Analiza empirică se bazează pe 3.443 de observații de tip firmă-an, corespunzătoare companiilor listate din industria textilă pe piața chineză A-share, pentru perioada 2014–2023 și utilizează modele cu efecte fixe bidirecționale. Rezultatele evidențiază că dezvoltarea finanțării digitale reduce semnificativ riscul financiar al firmelor textile. Testele privind mecanismele de influență arată că acest efect este mediat de reducerea asimetriei informaționale și de relaxarea constrângerilor de finanțare, cele două canale acționând complementar. Analiza heterogenității indică faptul că efectul de diminuare a riscului este mai pronunțat în regiunile centrale și vestice, în cazul firmelor cu o expunere mediatică mai ridicată, al întreprinderilor private și al firmelor mari. Rezultatele furnizează contribuții teoretice și implicații practice pentru firmele textile interesate de optimizarea strategiilor de finanțare și de consolidarea capacității de gestionare a riscului, cât și repere utile pentru elaborarea politicilor menite să sprijine transformarea digitală și dezvoltarea de înaltă calitate a industriei textile.

Cuvinte-cheie*: firme din lanțul valoric al textilelor, finanțare digitală, risc financiar, asimetrie informațională, constrângeri de finanțare*

INTRODUCTION

The textile industry, a quintessential labour-intensive sector, occupies a pivotal position in the global manufacturing system [1]. According to World Trade Organisation statistics, textile and apparel trade consistently accounts for 5% to 7% of global merchandise trade, with direct employment exceeding 60 million people worldwide. However, textile firms generally face severe financial challenges, including restricted access to credit, substantial cash flow pressures, and limited risk resilience [2]. These firms typically lack sufficient collateral assets and exhibit low information disclosure transparency, making it difficult for traditional financial institutions to accurately assess their creditworthiness. Consequently, financial institutions adopt credit rationing strategies or require substantial collateral. Intensified financing constraints not only restrict firms' daily operations and technological upgrading but also significantly elevate financial risk levels, threatening their sustainable development. Against this backdrop, the rapid development of digital finance offers a promising avenue for alleviating the financial distress of textile firms. Through innovations such as big data risk assessment, supply chain finance, and mobile payments, digital finance can transcend the geographic and informational barriers of traditional financial services, providing more accessible and cost-effective financing channels for underserved customers. Therefore, systematically examining how digital finance affects textile firms' financial risk and the underlying mechanisms carries important theoretical and practical implications for understanding how digital technologies empower the real economy and optimise financial resource allocation.

From a theoretical perspective, digital finance's impact on corporate financial risk can be understood through two complementary frameworks: information asymmetry theory and financing constraint theory. Information asymmetry theory posits that information gaps between lenders and borrowers lead to adverse selection and moral hazard problems, which in turn trigger credit rationing and higher financing costs [3]. In the textile industry, information asymmetry is particularly acute due to firms' typically small scale, opaque financial information, and insufficient collateral assets. Traditional financial institutions primarily rely on hard information, namely financial statements, collateral, and third-party guarantees, for risk assessment. However, such information is often outdated and incomplete, failing to accurately reflect textile firms' operating performance and repayment capacity. Digital finance platforms integrate multidimensional soft information, including transaction records from e-commerce platforms, logistics data, tax records, and supply chain relationships, to construct more comprehensive and dynamic credit profiles. This big data and machine learning-based risk assessment model significantly reduces information acquisition costs and assessment errors, enabling financial institutions to more accurately identify firms' true risk levels. Improved information disclosure quality reduces capital costs and enhances resource allocation efficiency [4]. Thus, by improving the information environment, digital finance is expected to reduce textile firms' financing costs and the extent of credit rationing, thereby mitigating financial risk.

Financing constraint theory emphasises that the wedge between external and internal financing costs affects firms' investment decisions and financial stability [5]. Due to information asymmetry and agency problems, external financing costs typically exceed internal financing costs. This financing friction leads to underinvestment or excessive reliance on short-term debt, thereby increasing financial risk [6]. For textile firms, low industry profit margins, long asset turnover cycles, and pronounced seasonal fluctuations create high dependence on external financing. However, traditional financial systems provide relatively limited credit support to small and medium enterprises and labour-intensive industries, resulting in severe financing constraints for textile firms. Digital finance significantly eases these constraints by offering diversified, low-cost, and convenient financing channels. For instance, pure credit loans based on transaction flows and supply chain data directly address the core challenge of small and medium enterprises lacking collateral. Mobile payments and digital wallets improve capital turnover efficiency. Supply chain finance platforms transmit core enterprises' credit to upstream and downstream small and medium enterprises, expanding financing availability. These innovative financing models not only increase firms' liquidity reserves but also optimise capital structure and reduce dependence on single financing channels, thereby enhancing firms' capacity to cope with unexpected payment demands and market volatility, ultimately reducing financial risk.

Although the above theoretical frameworks provide important foundations for understanding the relationship between digital finance and corporate financial risk, existing empirical research exhibits three key limitations. First, current research adopts narrow theoretical perspectives. Most studies explain digital finance's economic consequences through either financing constraint theory or information asymmetry theory in isolation, potentially overlooking the interactive effects and relative importance of these mechanisms [7–9]. In practice, improved information asymmetry can reduce financial institutions' risk premiums, thereby easing financing constraints. Conversely, expanded financing channels incentivise firms to enhance information disclosure quality to secure better financing terms. Therefore, single-perspective approaches inadequately capture the complete picture of how digital finance affects corporate financial risk.

Second, the transmission mechanisms through which digital finance affects corporate financial risk remain unclear. While existing research documents that digital finance improves firms' financing and information environments, how these improvements specifically translate into reduced financial risk, and what the mediation process entails, remains ambiguous. Current literature emphasises direct effects while neglecting mechanism identification.

Specifically, digital finance may affect financial risk through multiple pathways. The first is an information mechanism: digital finance platforms leverage firms' transaction flows, supply chain data, and other alternative information to construct credit profiles, reducing information asymmetry between banks and firms, thereby decreasing credit rationing and risk premiums and ultimately improving cash flow stability and debt servicing capacity. The second is a financing mechanism: digital finance provides diversified, low-cost financing tools that directly alleviate financing constraints, enhancing firms' ability to meet unexpected payment obligations and reducing liquidity risk. Identifying these mediation mechanisms not only deepens theoretical understanding of digital finance's pathways but also provides micro-foundations for understanding how digital technologies reshape financial resource allocation.

Third, the boundary conditions under which digital finance affects corporate financial risk remain unclear. Existing research rarely examines conditions under which digital finance's impact on financial risk strengthens, weakens, or changes direction, limiting the theory's applicability and predictive accuracy. In reality, digital finance's risk-mitigating effects may vary significantly across firm characteristics, regional environments, and external monitoring intensity. For example, in regions with scarce traditional financial resources, digital finance may generate greater marginal utility. In firms subject to stronger external monitoring, digital finance's information transparency effects may be amplified. Across different ownership structures and firm sizes, digital finance's mechanisms may differ. The effectiveness of small and medium enterprise financing models depends heavily on the institutional environment and market structure [10]. Therefore, identifying these boundary conditions is crucial for understanding digital finance's mechanisms across contexts and enhancing theoretical precision.

Addressing these research gaps carries important theoretical and practical significance. Theoretically, integrating financing constraint theory and information asymmetry theory and systematically identifying digital finance's dual mechanisms for affecting corporate financial risk and their interactive effects advances theoretical development in digital finance research and deepens understanding of how financial technology reshapes corporate risk management. Simultaneously, identifying boundary conditions such as regional environment, external monitoring, ownership structure, and firm size enhances theoretical precision and predictive power. Practically, this research provides decision-making guidance for textile firms to optimise financing strategies and enhance risk management capabilities, while offering empirical evidence for regulators to improve digital finance infrastructure and formulate differentiated support policies.

Existing research extensively explores digital finance's impact on corporate behaviour. Scholars find that digital finance promotes innovation, improves investment efficiency, and enhances operating performance by reducing transaction costs, improving information transparency, and expanding financing channels [7, 8]. Fintech lenders possess distinct advantages in information processing speed and risk pricing accuracy, enabling them to serve customer segments that traditional banks struggle to reach. Recent research also finds that digital finance development improves firms' sustainability performance, indicating that digital finance affects not only financial decisions but also long-term development [11]. However, existing literature primarily examines digital finance's impact on positive outcomes such as innovation and investment efficiency, with less systematic examination from a risk management perspective of how digital finance affects corporate financial risk levels, especially in labour-intensive, severely financing-constrained industries like textiles, where this question remains inadequately addressed.

China's textile industry provides a unique research setting for testing the relationship between digital finance and corporate financial risk. First, as a quintessential labour-intensive industry, textiles' characteristics, including financing difficulties, lengthy supply chains, and thin profit margins, make it an ideal context for testing digital finance's risk management effects. Textile firms occupy important positions in global value chains yet face complex financing constraints and transformation pressures. These industry characteristics create high dependence on external financing while making firms more vulnerable to financing constraints and information asymmetry problems. Second, China's rapid digital finance development provides rich policy and temporal variation for research. China's innovative practices in digital finance, including third-party payments, online lending, and supply chain finance, offer quasi-experimental variation for testing digital finance's impact on corporate financial risk. Third, significant differences in economic development levels, financial market maturity, and institutional environments across Chinese regions provide natural experimental settings for testing heterogeneous effects of digital finance. This research setting not only carries local practical significance but also provides important evidence for the international academic community to understand digital finance's mechanisms in emerging markets and labour-intensive industries.

To address these research gaps, this study examines digital finance's impact on textile firms' financial risk, including underlying mechanisms and boundary conditions. Based on financing constraint theory and information asymmetry theory, we construct an integrated analytical framework, proposing that digital finance reduces corporate financial risk through two pathways: easing financing constraints and alleviating information asymmetry. This study uses data from Chinese A-share textile industry listed companies from 2014 to 2023. The sample covers textiles and related supply chain industries, containing 3,443 firm-year observations. We employ two-way fixed effects models to identify the causal effect of digital finance on corporate financial risk and conduct robustness checks using lagged variables and prefecture-level fixed effects. Results show that digital finance development significantly reduces textile firms' financial risk levels. Mechanism tests indicate that digital finance operates through two pathways, namely reducing information asymmetry and easing financing constraints, with these pathways exhibiting complementary effects. Further heterogeneity analysis reveals that digital finance's risk-mitigating effects are more pronounced in central and western regions, firms with higher media attention, non-state-owned enterprises, and large firms. These findings remain robust after controlling for firm size, leverage, equity structure, and other factors, and pass multiple robustness checks, including lagged variables and prefecture-level fixed effects.

This research makes several theoretical contributions. First, it extends the theoretical boundaries of research on digital finance's economic consequences. Although digital finance theory is widely applied to explain positive outcomes such as innovation and investment efficiency, its applicability in risk management remains insufficiently tested. By empirically testing the relationship between digital finance and financial risk in textile industry samples, this research expands digital finance theory's scope. The textile industry, with its labour-intensive and capital-intensive characteristics, financing difficulties, lengthy supply chains, and thin profit margins, provides an ideal setting for testing digital finance's risk management effects. Existing research suggests that financial innovation's impact may differ significantly across industries. This research finds that digital finance significantly reduces financial risk even in textiles' unique context, demonstrating digital finance's risk-mitigating effects' strong generalizability while revealing unique mechanisms in labour-intensive industries.

Second, this research reveals digital finance's dual mechanisms for affecting corporate financial risk. Although existing research documents that digital finance affects corporate behaviour, the underlying mechanisms remain unclear. This research finds that digital finance affects financial risk through two pathways: an information mechanism and a financing mechanism. The information mechanism operates through digital finance platforms leveraging big data risk control technology to reduce information asymmetry between banks and firms, decreasing credit rationing and risk premiums and improving cash flow stability. Improved information disclosure quality reduces capital costs and enhances market liquidity [4]. The financing mechanism operates through digital finance, providing diversified, low-cost financing tools that directly ease financing constraints and enhance the capacity to meet unexpected payment demands. Financing constraints significantly affect firms' investment decisions and financial stability [6]. Empirical results support both pathways with complementary effects. Identifying these mediation mechanisms not only deepens theoretical understanding of digital finance's pathways but also provides microfoundations for understanding how financial technology reshapes corporate risk management.

Third, this research identifies important boundary conditions for digital finance's impact on corporate financial risk. Specifically, in central and western regions where traditional financial resources are relatively scarce, digital finance generates greater marginal utility with more pronounced risk-mitigating effects. In firms with higher media attention, external monitoring pressures reinforce digital finance's information transparency effects, consistent with existing findings on external governance mechanisms' roles [12–14]. In non-state-owned enterprises lacking implicit government guarantees, digital finance's financing channel expansion proves more critical. In large firms, more sophisticated internal management systems enable fuller utilisation of digital finance tools. By clarifying these boundary conditions, this research enhances digital finance theory's precision in predicting risk management effects and provides new evidence for understanding complementary or substitution relationships between information and financing mechanisms across contexts.

Fourth, this research provides a new theoretical perspective on the relationship between digital finance and corporate sustainability. By revealing how digital finance reduces corporate financial risk, this research provides new empirical evidence for understanding how digital technologies enhance firm resilience and promote sustainable development. Reduced financial risk not only directly improves firms' survival capacity and development potential but also creates more stable financial foundations for long-term investment, technological innovation, and sustainability practices. Practically, this research helps textile firms optimise digital finance application strategies according to their characteristics and external environments, while providing a reference for regulators to formulate differentiated digital finance support policies.

The remainder of this article proceeds as follows. Section 2 reviews related literature and develops research hypotheses based on theoretical analysis. Section 3 introduces the research design, including sample selection, variable measurement, and econometric model specification. Section 4 reports empirical results, including baseline regressions and robustness tests. Section 5 conducts mechanism and heterogeneity analyses. Section 6 concludes by summarising the theoretical and practical implications of research findings and identifying research limitations and future research directions.

THEORETICAL ANALYSIS AND RESEARCH HYPOTHESES

Digital finance and corporate financial risk

Corporate financial risk refers to the probability that a firm experiences financial distress, declining debt servicing capacity, or even bankruptcy due to various uncertainties in business operations [15]. For textile firms, financial risk is particularly acute due to distinctive industry characteristics and operational environments [16, 17]. The textile industry, characterised as labour-intensive with predominantly small and medium enterprises, lengthy supply chains, and narrow profit margins, commonly faces restricted credit access, substantial cash flow pressures, and limited risk resilience. Traditional financial systems provide relatively limited credit support to small and medium enterprises and labour-intensive industries, resulting in severe financing constraints for textile firms. Simultaneously, small firm size, opaque financial information, and insufficient collateral exacerbate information asymmetry, further intensifying financing difficulties and financial risk.

The rapid development of digital finance offers promising avenues for alleviating textile firms' financial distress. Digital finance encompasses financial services delivered through digital technologies such as the internet, big data, cloud computing, artificial intelligence, and blockchain, including digital payments, online lending, supply chain finance, and equity crowdfunding [8]. Compared with traditional finance, digital finance offers advantages of broad coverage, low cost, high efficiency, and minimal barriers to entry, transcending geographic and informational constraints of traditional financial services to provide more accessible and cost-effective financing channels for underserved customers [7].

From a theoretical perspective, digital finance's impact on corporate financial risk can be understood through two complementary dimensions. The first dimension draws on information asymmetry theory, which posits that information gaps between lenders and borrowers generate adverse selection and moral hazard problems, triggering credit rationing and elevated financing costs [3]. Digital finance platforms integrate multi-dimensional soft information, including transaction records from e-commerce platforms, logistics data, tax records, and supply chain relationships, to construct comprehensive and dynamic credit profiles. This big data and machine learning-based risk assessment model significantly reduces information acquisition costs and assessment errors, enabling financial institutions to more accurately identify firms' true risk levels. Improved information disclosure quality reduces capital costs and enhances resource allocation efficiency [4].

Therefore, by improving the information environment, digital finance is expected to reduce textile firms' financing costs and the extent of credit rationing, thereby mitigating financial risk.

The second dimension draws on financing constraint theory, which emphasises that the differential between external and internal financing costs affects firms' investment decisions and financial stability [5]. Due to information asymmetry and agency problems, external financing costs typically exceed internal financing costs. This financing friction leads to underinvestment or excessive reliance on short-term debt, thereby increasing financial risk [18]. Digital finance significantly eases these constraints by offering diversified, low-cost, and convenient financing channels. For instance, pure credit loans based on transaction flows and supply chain data directly address the core challenge of small and medium enterprises lacking collateral. Mobile payments and digital wallets improve capital turnover efficiency. Supply chain finance platforms extend anchor firms' credit to upstream and downstream small and medium enterprises, expanding financing availability. These innovative financing models not only increase liquidity reserves but also optimise capital structure and reduce dependence on single financing channels, thereby enhancing firms' capacity to cope with unexpected payment demands and market volatility, ultimately reducing financial risk.

Specifically, digital finance's risk-mitigating effects on textile firms manifest in several ways. First, digital finance facilitates capital flows throughout the textile supply chain. Textile firms typically operate within lengthy and complex supply chains spanning raw material procurement, production processing, distribution, and final consumption. Within this extensive network, capital flows directly determine supply chain efficiency and firm survival. However, traditional financial models often fail to meet the financing needs of various supply chain participants, impeding capital circulation and constraining supply chain development. Digital finance, leveraging advanced technologies such as big data and artificial intelligence, more precisely identifies financing needs across supply chain stages and delivers appropriate financial services. A stable and accessible financing environment enhances financing efficiency and reduces the likelihood of capital flow disruptions, playing a crucial role in textile firms' financial stability.

Second, diversified financing instruments provided by digital finance help textile firms manage seasonal and cyclical fluctuations. Textile firms frequently face seasonal and cyclical variations that significantly impact capital flows. Beyond traditional bank loans, digital finance offers diversified financing channels, including internet financial platforms with more flexible credit terms, equity crowdfunding, blockchain-based supply chain finance, and accounts receivable financing platforms. This diversification reduces dependence on a single financing source and enhances financing resilience. These financing instruments enable firms to obtain needed capital promptly while substantially reducing search, negotiation, and transaction costs, making small-scale, short-term, flexible financing feasible to support operational expansion during peak seasons and alleviate cash flow pressures during off-seasons. Through judicious use of these financing tools, firms can better manage capital flows and significantly reduce financing and operating costs. This not only directly enhances profitability but also substantially strengthens risk resilience, enabling firms to respond more effectively to market volatility and economic uncertainty, ensuring operational stability and sustainable development.

Third, digital finance development improves firm credit ratings and financing availability. Digital technology and platform economy development transcends traditional supply chain credit models centred on anchor firms, extending beyond original supply chain boundaries to enable credit circulation and expand the scope of industrial digital finance. Large numbers of firms access industrial internet platforms, achieving supply chain transparency [19]. Without relying on anchor firm credit enhancement, firms can convert their own commercial credit into financial credit to obtain financing, alleviating operational risks stemming from inadequate credit guarantees, insufficient collateral, and limited financing scope [20]. Through comprehensive firm evaluation, lenders identify high-quality borrowers, reducing borrower risk through improved counterparty selection and enabling capital to flow with lower risk, thereby enhancing risk resilience. Both capital suppliers and demanders reduce their respective risks through digital finance applications, enabling optimal allocation of limited resources. This helps firms obtain better-matched financing sources, improving cash flow sustainability and thereby achieving healthy operational development. Simultaneously, enhanced information transparency and regulatory oversight in financial markets help reduce information asymmetry and moral hazard, further lowering firms' financial risk.

Based on this analysis, we propose the following hypothesis:

Hypothesis 1: Digital finance development significantly reduces textile firms' financial risk levels.

The mediating role of information asymmetry

Information asymmetry constitutes a fundamental source of financial risk for textile firms. Information asymmetry theory posits that when transacting parties possess unequal information, market failures and resource allocation inefficiencies arise. In financial markets, information asymmetry primarily manifests as borrowing firms possessing superior knowledge of their true operational conditions, repayment capacity, and risk levels compared to lending institutions. This information differential generates adverse selection and moral hazard problems [3]. For textile firms, high information opacity stems from complex supply chains and vulnerability to raw material price and demand fluctuations. Banks and other traditional financial institutions struggle to accurately assess textile firms' true operational performance, repayment capacity, and prospects. Exercising risk aversion, they adopt credit rationing or require substantial collateral or guarantees, resulting in costly and restricted credit access. This directly elevates firms' leverage risk, liquidity risk, and refinancing risk.

Information asymmetry affects not only external financing but also internal governance. Within firms, principal-agent problems generate information asymmetry between shareholders and managers and between controlling and minority shareholders, increasing agency costs [21]. Managers may engage in opportunistic behaviours such as overinvestment, excessive perquisite consumption, or earnings management to maximise personal interests, harming shareholder value. Controlling shareholders may exploit their authority through related-party transactions and fund appropriation to expropriate minority shareholders. These agency problems reduce investment efficiency and cause resource misallocation, potentially leading to declining profitability and deteriorating cash flows, ultimately increasing operational and bankruptcy risk.

Digital finance development provides novel technological approaches to alleviating information asymmetry. Digital finance platforms leverage massive, real-time, unstructured data, including transaction records from e-commerce platforms, logistics information, tax data, and social media activity, to construct comprehensive digital profiles that more accurately and dynamically reflect firms' operating profitability, cash flow status, contract performance, and supply chain relationship stability. This big data and machine learning-based credit evaluation model reduces external investors' costs and difficulties in obtaining soft information about firms, transcending the limitations and lag of traditional financial statements. Existing research demonstrates that fintech lenders possess distinct advantages in information processing speed and risk pricing accuracy, enabling them to serve customer segments that traditional banks struggle to reach [7].

A more transparent information environment not only improves external financing conditions but also strengthens internal governance. When operational information becomes more transparent, managers' and controlling shareholders' behaviours face greater external scrutiny. Market reputation mechanisms and potential financing constraints discipline managerial opportunism and shareholder expropriation. Improved information disclosure quality reduces agency costs and enhances corporate governance, thereby avoiding principal-agent problems, achieving optimal resource allocation, improving decision-making and operational efficiency, supporting sustainable development, and reducing the probability of financial distress.

Specifically, digital finance reduces financial risk through alleviating information asymmetry via several mechanisms. First, credit evaluation models constructed by digital finance platforms using big data technology more accurately identify firms' true risk levels, reducing financial institutions' risk premiums and thereby lowering firms' financing costs. Lower financing costs directly improve cash flow conditions and relieve financial pressure. Second, a more transparent information environment reduces credit rationing and enhances financing availability. When financial institutions can more accurately assess firm risks, they become more willing to extend credit to high-quality firms, thereby easing financing constraints. Third, enhanced information transparency strengthens external monitoring, constraining opportunistic behaviours by managers and controlling shareholders, reducing agency costs, and improving resource allocation and operational efficiency. Higher operational efficiency and more robust cash flows jointly reduce financial risk.

Based on this analysis, we propose the following hypothesis:

Hypothesis 2: Digital finance reduces textile firms' financial risk by alleviating information asymmetry.

The mediating role of financing constraints

Financing constraints refer to difficulties firms face in obtaining capital for investment and operations when external financing costs exceed internal financing costs [22]. Financing constraint theory emphasises that, due to information asymmetry and agency problems, external financing costs typically exceed internal financing costs, and this financing friction affects firms' investment decisions and financial stability [5]. When facing financing constraints, firms may be forced to forego positive net present value investment projects or rely excessively on short-term debt and internal cash flows, thereby increasing financial risk [6].

Textile firms face particularly severe financing constraints. First, as a labour-intensive industry, textiles exhibit relatively low profit margins, lengthy asset turnover cycles, and pronounced seasonal fluctuations, creating high dependence on external financing. However, traditional financial systems provide relatively limited credit support to small and medium enterprises and labour-intensive industries. Financial market imperfections result in limited equity and debt financing channels with high barriers to entry. Bank credit further widens access disparities across ownership structures and firm sizes due to information asymmetry and banks' preference for state-owned, large-scale enterprises. Second, textile firms typically lack sufficient collateral and exhibit opaque financial information, making it difficult for traditional financial institutions to accurately assess creditworthiness, resulting in credit rationing or requirements for substantial guarantees. Intensified financing constraints not only restrict daily operations and technological upgrading but also significantly elevate financial risk levels.

Digital finance development provides novel approaches to easing financing constraints. Digital finance offers innovative financing models, reaches more underserved customers, and broadens textile firms' financing channels. Risk control models built on big data from transaction flows, payments, tax records, and supply chains enable unsecured, pure credit loans that directly address the core challenge of small and medium enterprises lacking collateral. Existing research demonstrates that fintech development has significantly reduced financing barriers for small and medium enterprises and improved financing availability [8]. Accessible financing channels provide important external liquidity sources, helping firms smooth operating cash flow volatility and enhance capacity to meet unexpected payment demands such as equipment maintenance and environmental compliance.

Digital finance eases financing constraints through several mechanisms. First, digital finance provides diversified financing channels, including internet financial platforms, equity crowdfunding, supply chain finance, and accounts receivable financing, reducing dependence on single financing sources and enhancing financing resilience. These financing instruments substantially reduce search, negotiation, and transaction costs, enabling small-scale, short-term, flexible financing. Second, digital finance platforms leverage big data risk control technology to more accurately assess credit status and repayment capacity, thereby reducing financing barriers and costs. Pure credit loans based on transaction flows and supply chain data directly address the core constraint of small and medium enterprises lacking collateral. Third, digital finance's efficiency and convenience enable firms to quickly obtain capital support [23], promptly addressing operational funding needs and avoiding missed development opportunities or financial distress due to capital shortages.

Easing financing constraints significantly reduces financial risk. Accessible financing channels provide important external liquidity sources, helping firms smooth operating cash flow volatility and enhance their capacity to meet unexpected payment demands. Additionally, efficient resource allocation optimises payment cycles and improves working capital efficiency for upstream suppliers and downstream customers, reducing uncertainty in capital circulation. Healthier capital structure, more robust cash flows, and stronger profitability jointly enhance overall financial resilience and risk-bearing capacity [24]. Existing research demonstrates that easing financing constraints significantly improves investment efficiency and operating performance while reducing financial risk [22].

Based on this analysis, we propose the following hypothesis:

Hypothesis 3: Digital finance reduces textile firms' financial risk by easing financing constraints.

RESEARCH DESIGN

Sample selection and data sources

This study examines A-share listed firms in China's textile and related value chain industries from 2014 to 2023 [1]. Firm-level financial data are obtained from the China Stock Market & Accounting Research (CSMAR) database, while digital finance indicators are drawn from the Digital Financial Inclusion Index published by the Institute of Digital Finance at Peking University. We apply the following screening criteria to the initial sample: (1) exclude specially treated (ST and *ST) firms; (2) exclude firms with missing financial data; and (3) winsorize all continuous variables at the 1st and 99th percentiles to mitigate the influence of outliers. These procedures yield a final sample of 3,443 firm-year observations.

Variable measurement

Dependent Variable: Firm Financial Risk (Z). To measure firm financial risk, this study employs the Z-Score method [25,26], calculated as follows:

$$Z = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 0.999X_5 \quad (1)$$

where X_1 = Working Capital/Total Assets, capturing asset liquidity and firm size; X_2 = Retained Earnings/

Total Assets, reflecting cumulative profitability; X_3 = EBIT/Total Assets, measuring asset profitability; X_4 = Market Value of Equity/Book Value of Total Liabilities, a financial structure ratio indicating the relationship between equity and debt, thereby measuring solvency; and X_5 = Operating Revenue/Total Assets, capturing asset turnover and the efficiency of asset utilization.

Independent Variable: Digital Finance Development (Index). We employ the Digital Financial Inclusion Index compiled by the Institute of Digital Finance at Peking University, which represents the most widely adopted measure of regional digital finance development in China. The index incorporates multiple dimensions through a rigorous and objective methodology, aligning with international standards while better capturing China's institutional context. Given its comprehensive coverage and temporal consistency, we adopt this index (scaled by dividing by 100) to measure regional digital finance development.

Control Variables. To isolate the relationship between digital finance and firm financial risk, we include the following firm-level controls: (1) Firm Size (Size), measured as the natural logarithm of total assets; (2) Leverage (Lev), calculated as total liabilities divided by total assets; (3) Largest Shareholder Ownership (Top1), defined as shares held by the largest shareholder divided by total shares outstanding; (4) Listing Age (ListAge), measured as ln(current year − IPO year + 1); (5) Managerial Ownership (Mshare), calculated as shares held by directors and senior management divided by total shares outstanding; (6) Operating Cash Flow (Cashflow), defined as net cash flow from operations scaled by total assets; (7) Current Ratio (Liquid), calculated as current assets divided by current liabilities; and (8) Board Size (Board), measured as the natural logarithm of the number of directors. Additionally, we control for year and firm fixed effects.

Model specification

To examine the relationship between digital finance development and firm financial risk, we estimate the following baseline model:

$$Z_{i,t} = \beta_0 + \beta_1 Index_{i,t} + \beta_2 Control_{i,t} + \beta_3 Firm_{i,t} + \beta_4 Year_{i,t} + \varepsilon_{i,t} \qquad (2)$$

where Z-Score measures firm financial risk, *Index* denotes digital finance development, *Control* represents the vector of firm-level control variables, *Year* and *Firm* capture year and firm fixed effects respectively, and ε is the error term.

EMPIRICAL RESULTS

Descriptive statistics

Following Altman's benchmark thresholds, a Z-Score above 2.675 indicates financial health with low bankruptcy risk; a Z-Score between 1.81 and 2.675 suggests the firm is in a distress zone with potential financial vulnerability; and a Z-Score below 1.81 signals severe financial instability and high default risk. Figure 1 presents descriptive statistics for our main variables. The firm financial risk measure (Z) exhibits substantial heterogeneity, ranging from 0.009 to 31.636 with a mean of 5.029, indicating considerable variation in financial stability across sample firms. The digital finance index (Index) averages 2.582, with a minimum of 1.262 and a maximum of 3.597, reflecting substantial regional variation in digital finance development, though most cities demonstrate moderate to high development levels.

Correlation analysis

To examine correlations among variables and assess potential multicollinearity, we conduct a Pearson correlation analysis. Figure 1 presents the correlation matrix. The digital finance index (Index) is positively and significantly correlated with the firm financial risk measure (Z), indicating that higher digital finance development is associated with higher Z-scores (i.e., lower financial risk). This finding is consistent with our hypothesis. Additionally, all pairwise correlations are below 0.7, suggesting that severe multicollinearity is unlikely to bias our estimates.

Baseline regression results

Figure 2 presents baseline regression estimates of the effect of digital finance on firm financial risk in the textile industry. Panel A reports results without control variables, while Panel B includes the full set of firm-level controls. In Panel A, the coefficient on Index is positive and statistically significant, indicating that higher digital finance development is associated with greater Z-Scores. In Panel B, after including controls, the coefficient on Index remains positive and significant with a magnitude similar to Panel A, suggesting that our core finding is robust.

Robustness tests

First, the economic effects of digital finance typically manifest with a time lag, as impacts on firm financial health may not materialise contemporaneously. To better capture this temporal structure, we re-estimate our baseline model using a one-period lag of Index. Additionally, this specification helps mitigate potential reverse causality; namely, that improvements in firm financial health might stimulate digital finance adoption, thereby inducing endogeneity bias. Figure 3, Panel A, presents results using the lagged digital finance index. The coefficient on lagged Index remains positive and significant with a magnitude consistent with baseline estimates, indicating that the effect of digital finance on firm financial risk is persistent and robust to alternative temporal specifications.

Second, prefecture-level cities exhibit systematic variation in economic development, financial infrastructure, industrial composition, and institutional quality. These time-invariant regional characteristics may jointly influence both digital finance development and firm financial risk, potentially inducing omitted variable bias. To address this concern, we augment the baseline model with city fixed effects to absorb all time-invariant city-level heterogeneity. Figure 3,

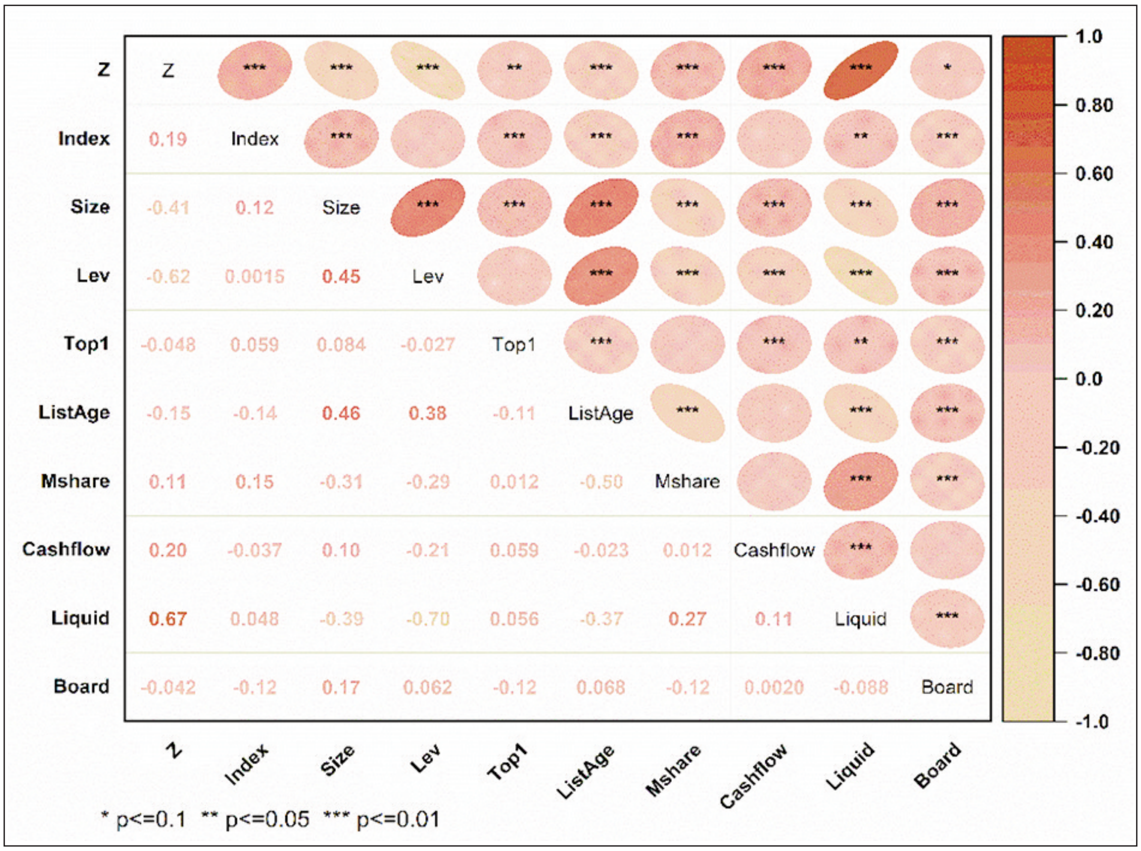

Fig. 1. Pearson correlation matrix

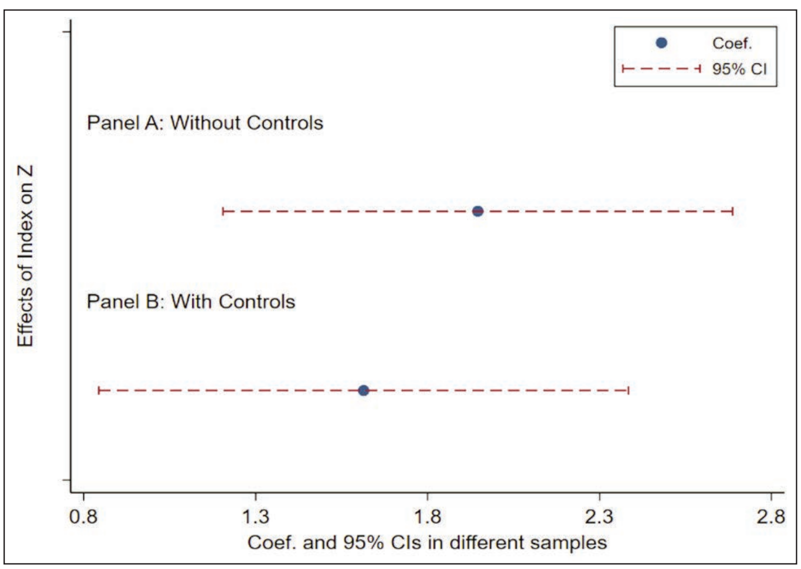

Fig. 2. Baseline regression results

Panel B reports estimates with city fixed effects. The coefficient on Index remains positive and significant, consistent with baseline results, confirming that our findings are robust to controlling for regional heterogeneity. This result suggests that time-invariant city characteristics do not drive our core findings.

FURTHER ANALYSIS

Mechanism analysis

To test whether information asymmetry and financing constraints mediate the effect of digital finance on firm financial risk, we employ the KV index and KZ index as mediators. The KV index measures firm-level information asymmetry [4], with higher values indicating greater opacity (or equivalently, lower transparency). The KZ index measures financing constraints, with higher values reflecting more severe constraints. To test these mediation channels, we estimate the following models:

$$M_{i,t} = \beta_0 + \beta_1 Index_{i,t} + \beta_2 Control_{i,t} + \beta_3 Firm_{i,t} + \beta_4 Year_{i,t} + \varepsilon_{i,t} \quad (3)$$

where M denotes the mediator, and all other variables are defined as in equation 2.

Figure 4, Panel A reports results for information asymmetry as the mediator. The coefficient on Index is negative and significant, indicating that digital finance reduces information asymmetry between financial institutions and firms. Reduced information asymmetry lowers risk assessment premiums and due diligence costs for lenders, mitigates market frictions, and improves credit terms. This facilitates efficient capital allocation, enhances firm profitability, and stabilises cash flows. Additionally, greater information transparency strengthens external monitoring and incentivises firms to improve corporate governance, thereby mitigating agency conflicts. These improvements enhance long-term firm value and financial resilience, ultimately reducing financial risk. These findings support Hypothesis 2.

Figure 4, Panel B, presents results for financing constraints as the mediator. The coefficient on Index is negative and significant, indicating that digital finance alleviates financing constraints by expanding firms' access to diverse, low-cost financing channels. Enhanced external liquidity enables firms to smooth cash flow volatility and reduce liquidity risk. Relaxed financing constraints also enable investment in operational improvements and innovation, boosting efficiency, competitiveness, and profitability. These factors jointly strengthen capital structure, stabilise cash flows, and enhance overall financial resilience. These findings support Hypothesis 3.

In summary, by reducing information asymmetry and alleviating financing constraints, digital finance enables textile firms to improve financial planning and resource allocation, thereby enhancing operational stability and financial resilience. These mechanisms allow firms to better navigate volatile market conditions and strengthen their capacity to manage financial risk.

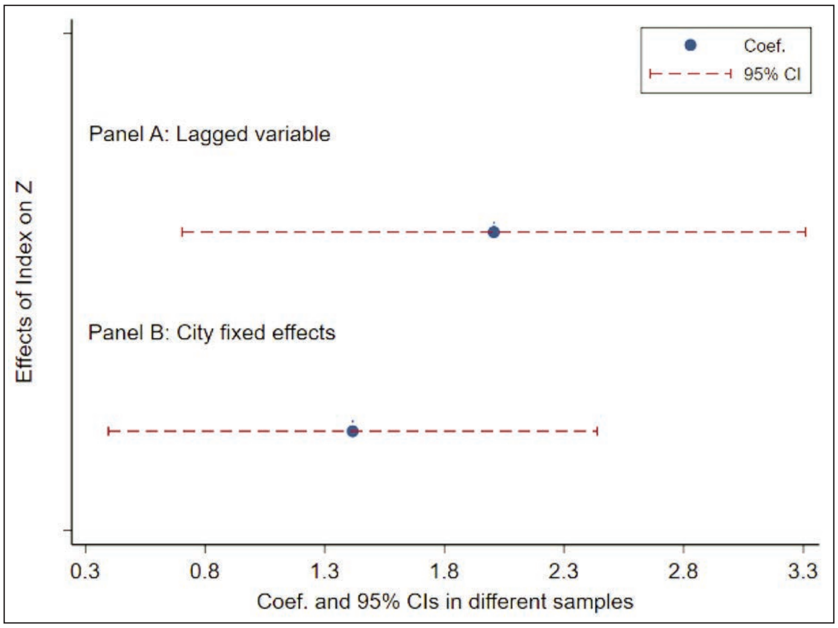

Fig. 3. Robustness testss

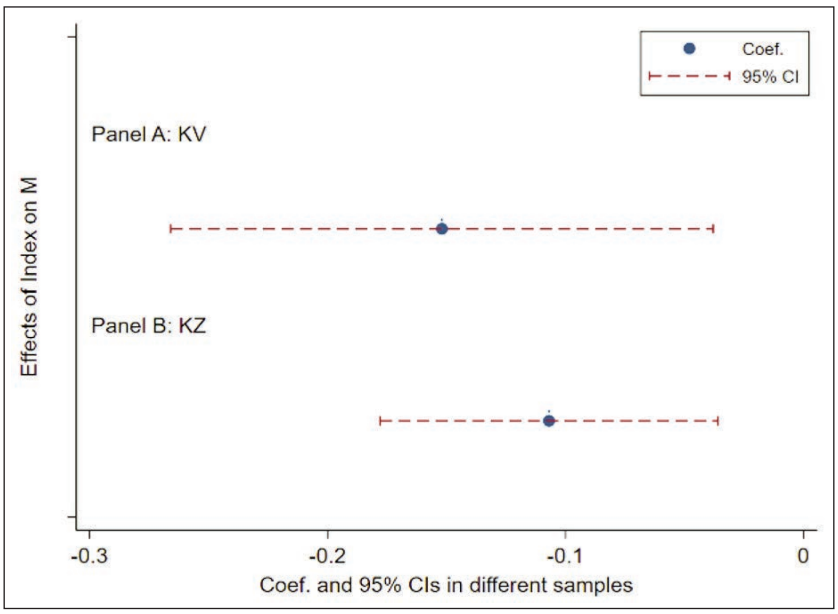

Fig. 4. Mechanism analysis

Heterogeneity tests

Regional economic development

To examine regional heterogeneity in the effect of digital finance on firm financial risk, we partition the sample by firm registration location into eastern regions versus central and western regions, and estimate separate regressions for each subsample. The coefficient on Index is positive but smaller in magnitude for eastern firms (significant at the 10% level), whereas the coefficient is larger and significant at the 1% level for firms in central and western regions. This pattern suggests that digital finance has a stronger risk-mitigating effect in less developed regions. One explanation is that eastern regions have more developed traditional financial markets, making firms less reliant on digital finance. In contrast, central and western regions have less developed traditional finance, so digital finance exhibits larger marginal effects in improving access to capital and reducing financial risk.

Media coverage

External monitoring intensity is a key determinant of capital allocation efficiency and firm financial risk. Media coverage not only reflects public attention but also influences firm behaviour and disclosure quality through monitoring and reputation effects. We measure media coverage using the total number of print and online news articles mentioning each firm, and partition the sample at the median. Figure 5, Panel B, shows that the coefficient on Index is positive and significant among high-coverage firms, but insignificant for low-coverage firms. This heterogeneity likely reflects that high media coverage strengthens external monitoring, incentivising firms to disclose more information and thereby reducing information asymmetry between firms and capital providers. In more transparent information environments, digital finance's advantages in information processing and capital allocation can be more fully realised, enhancing its effectiveness in reducing financing constraints and

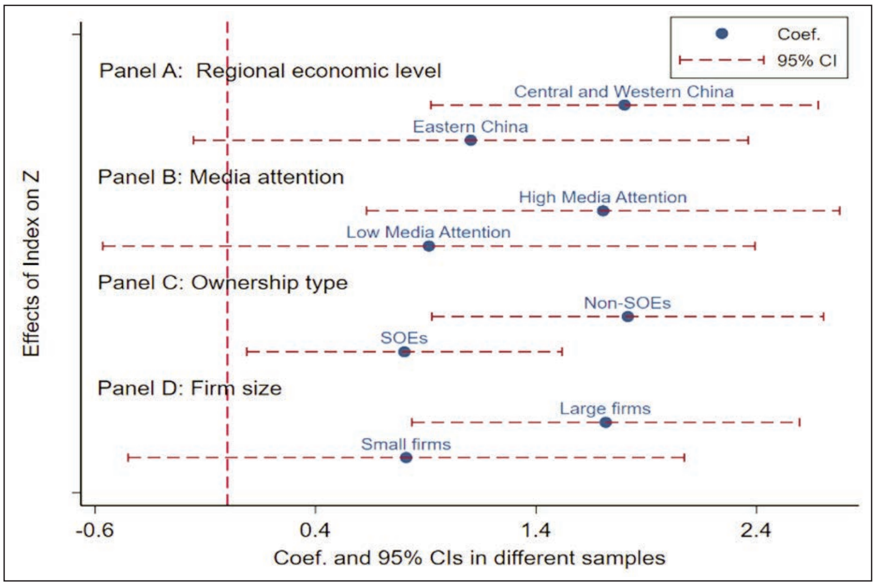

Fig. 5. Heterogeneity Analysis

financial distress. Conversely, low-coverage firms face weaker external monitoring and limited transparency. Although digital finance still improves financing access for these firms, its risk identification capabilities and capital allocation efficiency are constrained by information opacity, diminishing its effectiveness in reducing financial risk.

Ownership structure

Typically, non-state-owned enterprises (non-SOEs) face more severe financing constraints due to the lack of implicit government guarantees or backing, which limits their access to sufficient funding from mainstream financial institutions. Concurrently, heightened information asymmetry significantly escalates external financing costs, imposing an intangible burden that further exacerbates economic and financial pressures. Digital finance, leveraging advanced data capture and deep analytical capabilities, effectively alleviates financing constraints for non-SOEs, breaks development bottlenecks, and expands capital acquisition channels. By fundamentally mitigating information asymmetry, digital finance also suppresses tendencies toward underinvestment or inefficient allocation. This positive feedback mechanism renders non-SOEs more reliant on digital finance for daily operations and R&D innovation, ultimately leading to a robust reduction in financial risk.We partitioned the sample by ownership type into non-SOEs and SOEs to examine the differential impact of digital finance. As shown in figure 5 Panel C, the coefficient for digital finance is significantly positive at the 1% level for non-SOEs, whereas it is only significant at the 5% level for SOEs, with a marked disparity in the coefficient magnitudes. These results indicate that the risk-mitigating mechanism of digital finance is more potent in non-SOEs, highlighting a heterogeneous effect sensitive to ownership structure in terms of easing financing constraints and optimizing resource allocation.

Firm size

Firm size determines bargaining power in capital markets, financing channel diversity, and risk-bearing capacity, potentially moderating the effect of digital finance on financial risk. To test this, we partition the sample by firm size into large and small firms and estimate separate regressions. Figure 5, Panel D, shows that the coefficient on Index is positive and significant only for large firms, while the effect is insignificant for small firms. This heterogeneity likely reflects that large firms have more sophisticated management systems, greater financial transparency, and broader access to financing channels, enabling them to better leverage digital finance's capabilities in capital allocation and risk management, thereby reducing financial risk. Conversely, small firms face constrained access to capital, lower disclosure quality, and fewer managerial resources. Although digital finance still improves financing access for small firms, its marginal benefits are limited by these constraints, diminishing its effectiveness in reducing financial risk.

CONCLUSIONS AND POLICY IMPLICATIONS

This study examines data from Chinese A-share textile industry listed companies spanning 2014 to 2023 to investigate digital finance's impact on corporate financial risk and the underlying mechanisms. Three principal findings emerge. First, digital finance development significantly reduces textile firms' financial risk levels. Second, mechanism tests indicate that digital finance operates through two pathways, namely alleviating information asymmetry and easing financing constraints, with these pathways exhibiting complementary effects. Third, heterogeneity analysis reveals that digital finance's risk-mitigating effects are more pronounced in central and western regions, firms with higher media attention, non-state-owned enterprises, and large firms.

Theoretical contributions

This research makes several theoretical contributions.

First, this study extends the theoretical boundaries of research on digital finance's economic consequences. Although digital finance theory is widely applied to explain positive outcomes such as corporate innovation and investment efficiency, its applicability in risk management remains insufficiently tested. By empirically examining the relationship between digital finance and financial risk in textile industry samples, this research expands digital finance theory's scope. The textile industry, characterised by labour-intensive and capital-intensive operations, financing difficulties, lengthy supply chains, and narrow profit margins, constitutes an ideal setting for testing digital finance's risk management effects. Existing research suggests that financial innovation's impact may differ significantly across industries. This study finds that digital finance significantly reduces financial risk even within the textile industry's distinctive context, demonstrating that digital finance's risk-mitigating effects possess strong generalizability while revealing the unique mechanisms through which digital finance operates in labour-intensive industries.

Second, this research reveals digital finance's dual mechanisms for affecting corporate financial risk. Although existing research documents that digital finance influences corporate behaviour, the underlying mechanisms remain unclear. This study finds that digital finance affects financial risk through two pathways: an information mechanism and a financing mechanism. Through the information mechanism, digital finance platforms leverage big data risk control technology to reduce information asymmetry between banks and firms, decreasing credit rationing and risk premiums and improving cash flow stability. Improved information disclosure quality reduces capital costs and enhances market liquidity. Through the financing mechanism, digital finance provides diversified, low-cost financing instruments that directly ease financing constraints and enhance firms' capacity to meet unexpected payment demands. Financing constraints significantly affect firms' investment decisions and financial stability. Empirical results support both pathways operating simultaneously with complementary effects. Identifying these mediation mechanisms not only deepens theoretical understanding of digital finance's pathways but also provides microfoundations for understanding how financial technology reshapes corporate risk management.

Third, this research identifies important boundary conditions for digital finance's impact on corporate financial risk. Digital finance's effects on financial risk vary significantly across regional environments, external monitoring intensity, ownership structures, and firm sizes. In central and western regions where traditional financial resources are relatively scarce, digital finance generates greater marginal utility with more pronounced risk-mitigating effects. In firms with higher media attention, external monitoring pressures reinforce digital finance's information transparency effects, consistent with existing findings on the roles of external governance mechanisms. In non-state-owned enterprises lacking implicit government guarantees, digital finance's expansion of financing channels proves more critical. In large firms, more sophisticated internal management systems enable fuller utilisation of digital finance tools. By clarifying these boundary conditions, this research enhances digital finance theory's precision in predicting risk management effects and provides new evidence for understanding complementary or substitution relationships between information and financing mechanisms across contexts.

Fourth, this research provides a new theoretical perspective on the relationship between digital finance and corporate sustainable development. By revealing how digital finance reduces corporate financial risk, this study offers new empirical evidence for understanding how digital technologies enhance firm resilience and promote sustainable development. Reduced financial risk not only directly improves firms' survival capacity and development potential but also creates more stable financial foundations for long-term investment, technological innovation, and sustainability practices.

Policy implications

This study's findings carry important policy implications for firms, financial institutions, and government regulators.

Implications for firms

The findings regarding digital finance's dual mechanisms suggest that textile firms designing financing strategies should attend not only to broadening financing channels but also to improving information disclosure quality. Specifically, firms should proactively engage with digital finance platforms and accumulate digital footprints through e-commerce transactions and supply chain coordination to enhance the completeness and accuracy of their credit profiles. This proactive approach to information disclosure not only reduces financing costs but also strengthens trust relationships with financial institutions, thereby securing more stable financing support. The heterogeneity findings indicate that firms should calibrate their digital finance application strategies according to their characteristics and external environments. In central and western regions where traditional financial resources are scarce, firms can rely more heavily on digital finance channels. In environments with higher media attention, firms should complement digital finance with more comprehensive information disclosure to amplify digital finance's effects. Non-state-owned enterprises, lacking implicit government guarantees, should place greater emphasis on establishing market-based credit mechanisms through digital finance platforms. Large firms should leverage their managerial advantages and data resources to optimise financial management and risk control systems through digital means.

Implications for financial institutions

The finding that digital finance reduces corporate financial risk by alleviating information asymmetry and easing financing constraints points the way for financial institutions to innovate their products and services. Financial institutions should increase investment in big data risk control and artificial intelligence credit assessment technologies, developing more precise risk pricing models, particularly suited to small and medium enterprises and labour-intensive firms that traditional credit assessment systems struggle to serve. Supply chain finance represents an important innovation direction: by integrating transaction data from anchor firms and their supply chain partners, financial institutions can more accurately assess small and medium enterprises' true operational conditions and repayment capacity, enabling more flexible financing arrangements. The regional heterogeneity findings indicate that financial institutions should adopt differentiated market strategies, intensifying digital finance product promotion in central and western regions to fill gaps left by traditional financial services. Additionally, financial institutions should establish long-term cooperative relationships with firms, reducing information asymmetry through continuous data accumulation and credit building to achieve a better balance between risk and return.

Implications for government regulators

The finding that digital finance significantly reduces textile firms' financial risk provides empirical support for regulatory authorities formulating digital finance development policies. First, regulators should strengthen digital finance infrastructure, including information technology platforms, data sharing systems, and digital payment and risk management systems, particularly in central and western regions and areas with insufficient traditional financial coverage. Robust infrastructure ensures firms can access financial resources more conveniently and improves capital allocation efficiency. Second, regulators should promote deeper integration of digital finance with the real economy, using policy guidance to encourage financial institutions to provide more targeted financing solutions for small and medium enterprises and non-state-owned enterprises. The heterogeneity findings indicate that regulatory policies should not treat all firms uniformly but should formulate differentiated support policies according to regional environments and firm characteristics. For example, intensifying digital finance promotion in central and western regions, providing dedicated financing support for non-state-owned enterprises, and guiding large firms to leverage digital means to optimise financial management. Third, regulators should strengthen oversight and risk control of digital finance. Although digital finance helps reduce corporate financial risk, it may itself introduce systemic or operational risks. Relevant regulatory frameworks should be improved to strengthen information disclosure, data security management, and transaction monitoring, ensuring that digital finance maintains sound operation while improving firms' financing convenience. Regulatory authorities can also use policy guidance to standardise digital finance product design and application processes, preventing potential risks from excessive leverage or capital misallocation. Finally, regulators should establish evaluation frameworks for digital finance development, regularly monitoring digital finance's impact on different industries, regions, and types of firms, and adjusting policy directions promptly to ensure that digital finance genuinely serves the high-quality development of the real economy.

Research limitations and future directions

This research has several limitations that point to directions for future research.

First, regarding the measurement of financial risk, this study employs the Z-Score model to assess corporate financial risk levels. This model was developed based on data from U.S. manufacturing listed companies. Although the textile industry is part of the manufacturing sector, its specific operational characteristics, including high inventory turnover pressure, seasonal volatility, high sensitivity to raw material prices, substantial labour cost shares, and intense price competition, may differ significantly from those of the general manufacturing firms used to calibrate the model. The model's weights and thresholds may not fully capture the risk characteristics specific to the textile industry. Future research could construct risk indicator systems better suited to textile firms' characteristics, incorporating cash flow status, debt servicing capacity, and operational efficiency metrics to analyse digital finance's impact on textile firms' financial conditions more accurately and thereby provide more precise financial risk assessments.

Second, regarding the deepening of mechanism analysis, the mechanism tests in this study rely primarily on proxy variables for measurement, which represent a degree of approximation. Although this quantitative approach validates the mediating roles of the information mechanism and financing mechanism, it has difficulty fully capturing the specific decision-making considerations and cognitive factors firms encounter when facing digital finance development, as well as the potentially complex interactions between these two mechanisms. Future research could employ qualitative methods such as survey questionnaires, in-depth interviews, or case studies to investigate these issues more thoroughly, clarifying the sequencing and interactions between these two mechanisms to present a more complete picture of firms' actual decision-making processes.

Finally, regarding the research context generalizability, this study focuses on Chinese A-share textile industry listed companies. China's institutional environment has distinctive characteristics that may exert potential influence on research findings and thereby limit the direct generalizability of conclusions. China's top-down financial regulatory system and policy orientation may make firms more receptive to digital finance, potentially amplifying the observed effects. Additionally, the rapid development and widespread adoption of digital finance in China, which may be more mature than in other markets, could make digital technology-based risk mitigation mechanisms more effective. Furthermore, the sample is limited to publicly traded listed companies and does not encompass small and medium non-listed enterprises. Listed companies typically possess better information disclosure quality and stronger resource access capabilities, and their utilisation of and outcomes from digital finance may differ significantly from non-listed enterprises. When facing financing constraints, non-listed enterprises may rely more heavily on digital finance due to resource limitations or may be unable to fully leverage digital finance tools due to weaker digitalisation capabilities. Testing this study's findings in different institutional and organisational contexts is essential. Future research should conduct cross-country comparative studies in countries with differing degrees of financial market development, digitalisation levels, and regulatory environments, such as mature market economies in Europe and North America, or other emerging market economies. Equally important, future research should attempt to incorporate non-listed companies and small and medium enterprises into the analysis to examine the validity and generalizability of this study's proposed mechanisms across different organisational scales, ownership structures, and resource constraints. This would help validate the external validity of the core mechanisms identified in this research while providing opportunities to explore potential substitution or complementarity relationships between digital finance and traditional financial regulation and market mechanisms, thereby contributing to a more comprehensive understanding of digital finance's risk management effects in a global context.

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Research on colour matching recommendation for clothing users based on the DBSCAN clustering algorithm

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ABSTRACT – REZUMAT

Research on colour matching recommendation for clothing users based on the DBSCAN clustering algorithm

Colour plays an important role in promoting the sales relationship between clothing brands and users. This article is based on publicly available e-commerce image data from Tmall and the brand's official website. Taking the Taiping Bird brand as an example, a large amount of image data is preprocessed using the Structural Similarity SSIM index, which is used to evaluate image similarity. The image data is vectorised using a non-linear conversion formula from RGB format to HSV format, and K-means clustering analysis is performed to obtain the main colours of the image. Finally, the BDSCAN clustering algorithm is used to cluster the large amount of colour data, continuously modifying the neighbourhood threshold eps and minimum sample threshold minPts parameters until a sufficient number of clusters are obtained and a relatively low noise rate is achieved. Finally, for each category, a greedy algorithm is used to solve for the minimum subset of samples that can represent each cluster. The results are presented in the form of web pages, divided into two-page entrances for users and brand owners. It provides competitive brand colour recommendations and real-time sales to brand owners, and personalised colour preference recommendations and direct links to recommended products to users.

Keywords: *BDSCAN clustering algorithm, greedy algorithm, computer vision, clothing, colour matching recommendation*

Cercetare privind recomandările de asortare a culorilor pentru utilizatorii de îmbrăcăminte, pe baza algoritmului de grupare DBSCAN

Culoarea joacă un rol important în promovarea relației comerciale dintre brandurile de îmbrăcăminte și utilizatori. Acest articol se bazează pe date imagistice din comerțul electronic, disponibile public, provenite de pe Tmall și de pe site-ul oficial al brandului. Luând ca exemplu brandul Taiping Bird, o cantitate mare de date imagistice este preprocesată folosind indicele de similitudine structurală SSIM, utilizat pentru evaluarea similitudinii imaginilor. Datele de imagine sunt vectorizate folosind o formulă de conversie neliniară din formatul RGB în formatul HSV, iar analiza de grupare K-means este efectuată pentru a obține culorile principale ale imaginii. În cele din urmă, algoritmul de grupare BDSCAN este utilizat pentru a grupa cantitatea mare de date de culoare, modificând continuu parametrii pragului de vecinătate „eps" și pragul minim de eșantionare „minPts" până când se obține un număr suficient de grupuri și se atinge o rată de zgomot relativ scăzută. În cele din urmă, pentru fiecare categorie, se utilizează un algoritm de tip „greedy" pentru a determina subansamblul minim de eșantioane care poate reprezenta fiecare cluster. Rezultatele sunt prezentate sub formă de pagini web, împărțite în intrări de două pagini pentru utilizatori și proprietari de mărci. Recomandări competitive privind culorile mărcii și vânzări în timp real sunt oferite proprietarilor de mărci, precum și recomandări personalizate privind preferințele de culoare și linkuri directe către produsele recomandate utilizatorilor.

Cuvinte-cheie*: algoritmul de grupare BDSCAN, algoritm de tip „greedy", viziune computerizată, îmbrăcăminte, recomandări privind asortarea culorilor*

INTRODUCTION

The style, colour, and pattern of clothing are collectively known as the three key elements of fashion. These elements are not only crucial criteria for consumers when making purchasing decisions but also vital considerations for brands during the design and production process. Against the background of the rapid development of the Internet, the clothing industry, as an important part of the traditional manufacturing industry, has also faced huge development challenges [1]. Consumers' colour preferences for clothing vary across different seasons and times. For example, in summer, consumers tend to prefer light colours with low saturation that evoke a sense of calm, while in autumn, they favour warm and stable colours like warm browns or black. For brands, understanding the current colour preferences of consumers is a crucial task. For consumers, while following trends, maintaining their own colour preferences without blindly following the crowd is an important consideration in life. To meet these needs, marketing channels are diversified, including vertical chain, franchise, direct sales, commission sales, and horizontal online businesses, stores and webchat business, etc., which need different business methods to gradually innovate [2].

The so-called colour marketing is that enterprises use consumers' emotional demands to integrate colours, realize the organic unity of items, colours and people, to attract consumers' attention, promote consumer consumption, strengthen consumers' impression of the brand, and make consumers form a chain reaction of thinking on the colour, to realize the purpose of long-term stable development of enterprises and maximize the efficiency of commodity marketing [3]. Brand designers need to consider consumers' age, gender, psychological needs, cultural background and other differences, as well as consumers' experience of colour [4].

With the rapid development of computer technology and major e-commerce platforms, both brands and customers have more ways and methods to analyse market data and make choices. For brands, understanding the marketing market and the colour needs and preferences of consumers is essential for increasing sales. During the marketing process, colour is used to convey the company's image, complete product packaging design, advertising, and to effectively connect with the market [5]. For consumers who follow market trends and pursue individuality, appropriate colour references are also an indispensable part. With the widespread use of social media and its deep integration into everyday life, consumer engagement has reached unprecedented levels. Consumers are more inclined to use social media and online reviews to gather product information, which significantly influences their purchasing decisions [6].

The combination of computer vision and neural network algorithms has become a popular research method. For instance, Shuguang et al. utilised an improved VGGNet neural network combined with YOLOv3, Faster R-CNN, and SSD object detection algorithms to achieve pattern recognition and localisation [7]. Liang developed a computer colour matching system design based on machine learning, which, by continuously collecting user feedback, imitates the decision-making patterns of human designers in the colour matching process, thereby optimising colour matching schemes and providing efficient and personalised colour matching suggestions to better meet consumer needs [8]. Yani, based on deep learning knowledge, proposed a colour matching board generation network (SPCPN) that integrates user emotions with popular colours and colour matching rules, and an interactive fabric image colour matching network (IFCN). She built an intelligent fabric colour matching system based on Pyqt5, realising an interactive intelligent fabric colour matching system primarily aimed at designers [9].

It is not difficult to see that the data information contained in the open network can be used to identify the interests, needs and behaviour habits of the target audience through data analysis technology, so as to realise the push of personalised content and the accurate dissemination of marketing information. This personalised marketing strategy not only improves the information arrival rate, but also enhances the user's sense of participation and satisfaction [10]. Therefore, enterprises urgently need to use digital means to improve the quality of products and services. Relying on advanced digital technologies, companies can precisely monitor market dynamics and consumer preferences [11].

In this study, a hierarchical colour analysis framework is proposed, which combines K-means++ with the DBSCAN density clustering algorithm and is applied to the field of clothing colour recommendation. In the implementation of the traditional K-means algorithm, the sample data is assumed to be spherical clusters. However, clothing colour often presents complex distribution in HSV space, such as multimodal characteristics of young women's clothing. DBSCAN automatically identifies arbitrary shape clusters and separates noise through density threshold, and combines K-means++ for dominant colour extraction, which significantly improves the robustness of feature representation.

And, existing tools like Huemint and Palettemaker only provide static colour schemes. The platform integrates consumer demand and click volume, dynamically displays the seasonal colour migration trajectory, and supports real-time screening of user preferences. Compared with commercial software, this platform realises cross-category adaptive recommendation, such as the independent modelling of the colour scheme of young women's clothing and the monochromatic business style of men's clothing, which provides ideas for the colour matching of subsequent clothing colours in a single category.

RESEARCH PRINCIPLES

The data used in this study were sourced from the Tmall e-commerce platform and the official websites of various brands.

The dataset plays a crucial role in the outcomes of machine learning, and web data obtained via web scraping tools may contain duplicates, damage, or low-resolution issues. This paper employs the Structural Similarity Index (SSIM) to perform data cleaning on a large set of image data. Samples with SSIM $\geq$ 0.9, low pixel count, or damage are removed before selecting the primary colours of the images. The RGB format is converted to HSV format using a linear transformation formula, which avoids the issues of high correlation between indicators and human visual errors inherent in the RGB colour space. Subsequently, K-means clustering analysis is conducted to extract the cluster centres as the main colours of these images. After obtaining the main colours of the images, the BDSCAN clustering algorithm is applied to cluster the colour data, continuously adjusting the neighbourhood threshold eps and the minimum sample threshold *minPts* parameters until a suitable number of clusters is obtained with a relatively low noise rate. Finally, a greedy algorithm is used for each category to find the smallest sample subset that best represents each cluster (figure 1).

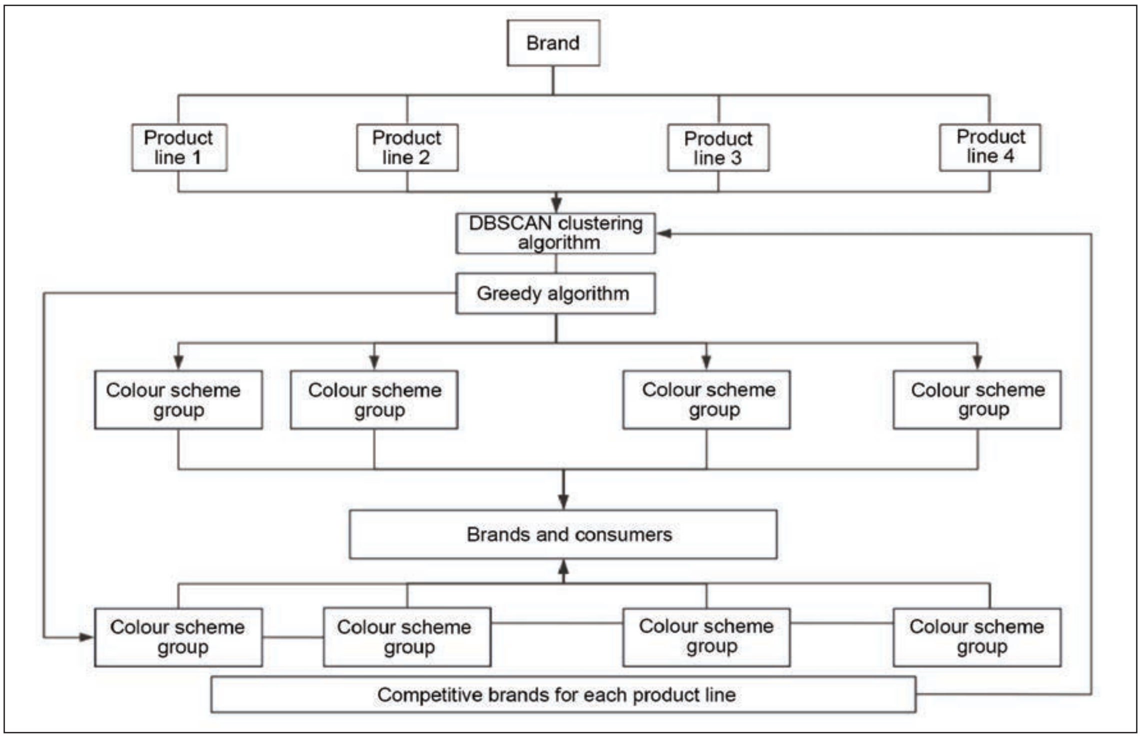

Fig. 1. Schematic diagram of the research process

Data cleansing

The selection of data is crucial to the effectiveness of algorithm models. Common image processing methods based on web crawler technology include up and down flipping, mirror flipping, adding salt and pepper noise and other preprocessing and data enhancement operations [12]. Considering the redundancy, duplication, and low-resolution images on websites, this paper adopts the Structural Similarity Index (SSIM). By calculating the average luminance of the images (σ_x, σ_y), the standard deviation of image luminance (μ_x, μ_y), and the luminance covariance between two images (σ_{xy}), and combining these with the simplified SSIM (formula 1) results, the similarity between images is evaluated. Images with a similarity above 0.9 are removed.

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)} \quad (1)$$

$$\text{where } C_1 = (k_1L)^2,\ C_2 = (k_2L)^2,$$

and $L = 2^B - 1$ (image pixel range), $k_1 = 0.01$, $k_2 = 0.03$

Additionally, images with a resolution lower than 10*10 pixels and damaged images are removed to ensure the stability and accuracy of the model. The number of images after cleaning is shown in table 1, and the cleaned data are used as the input samples for machine learning.

Table 1

DATA CLEANING RESULTS (PART 1)

Brand	Before washing	After washing
PEACEBIRD Women	2944	2848
PEACEBIRD Men	2605	2450
PEACEBIRD Kids	2092	2003
Ledin	2960	2753

Table 2

DATA CLEANING RESULTS (PART 2)

Brand	Before washing	After washing
Zara & Ochirly	2528	2311
Youngor & GXG	8276	7252
Balabala & Annil	6809	5206
Elf Sack & H&M	2685	2144

Basic algorithms

RGB model and HSV model

The RGB model (figure 2) is a commonly used colour representation model composed of three channels of data, red, green, and blue, the three primary colours of light, which are combined to form visible colours. The RGB model is widely used for colour storage and computation within computers, with the advantage of being intuitive and easy to understand. However, the three variables that make up the model are highly correlated, meaning that a change in one channel can potentially affect the values of the other two channels. The difference between colours cannot be measured by the distance between RGB values, and the same RGB values can display differently on different devices, making it unsuitable for standardised representation and inter-device communication.

On the other hand, the HSV model (figure 3) defines colour by hue, saturation, and brightness, which not

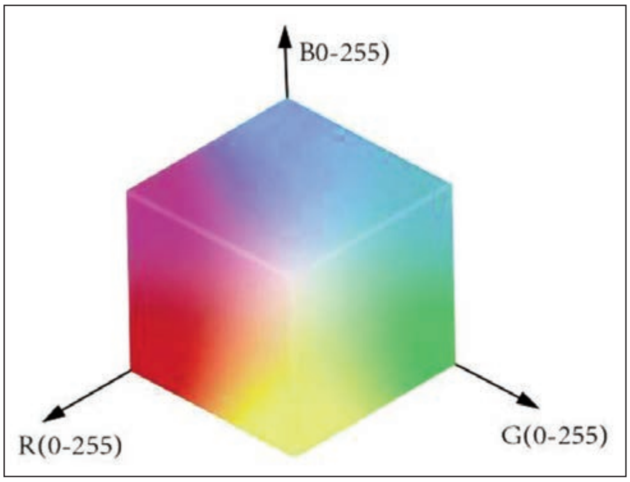

Fig. 2. RGB colour space model

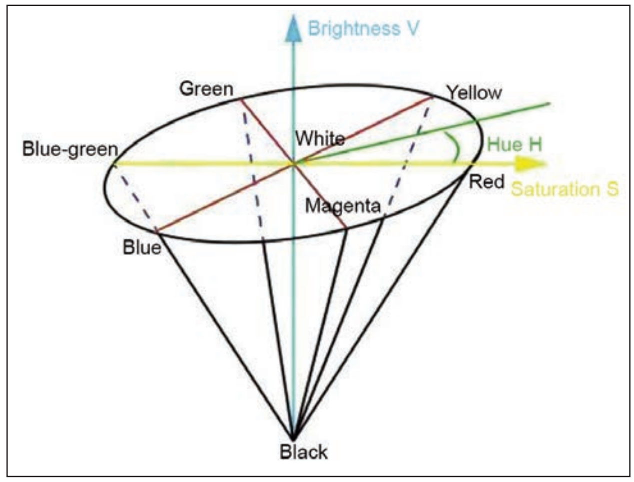

Fig. 3. HSV colour space model

only avoids the issue of high correlation in RGB channels but also makes colour representation closer to what the human eye perceives. Hue represents the type of colour perceived by the human eye, with the entire hue circle being a central angle of 360◦, where different angles correspond to different colours perceived by the human eye; brightness represents the lightness or darkness of the colour; and saturation represents the purity of the colour [13]. After transformation, the RGB data stored within the computer can be non-linearly mapped into the HSV colour space. The specific steps for this are:

Normalisation of RGB (formula 2)

$$R' = \frac{255}{R},\ G' = \frac{255}{G},\ B' = \frac{255}{B} \tag{2}$$

where R, G, and B represent the corresponding three-channel data in the RGB colour model of the image.

Calculation of Brightness V (formula 3)

$$V = \max(R',G',B') \tag{3}$$

3. Calculation of Saturation S (formula 4)

$$S = \frac{V - \min(R',G',B')}{V} \tag{4}$$

4. Calculation of Hue H (formula 5)

$$H = \begin{cases} 60° \times \left(\frac{G' - B'}{V - \min(R',G',B')}\right) \bmod 6 & \text{if } V = R' \\ 60° \times \left(\frac{B' - R'}{V - \min(R',G',B')} - 2\right) & \text{if } V = G' \\ 60° \times \left(\frac{R' - G'}{V - \min(R',G',B')} + 4\right) & \text{if } V = B' \end{cases} \tag{5}$$

METHODS

Colour extraction in computer vision

This paper opts to perform computer vision analysis in the HSV colour space. Using a nonlinear transformation formula from RGB to HSV format, the image data is vectorised, and a two-dimensional array is created for each image [14, 15]. The vectorised image data is then subjected to K-means clustering analysis, with the cluster centres formed by this unsupervised algorithm extracted as the main colours of the image. The primary steps of the K-means algorithm are as follows:

1. Random initialisation: randomly select K data points from the dataset as initial cluster centres, where K represents the target number of clusters.
2. Assignment: assign each data point to the nearest category based on distance D_i, using the Euclidean distance (formula 6), where x_i and y_i are corresponding indicators of the same dimension in different two-dimensional arrays:

$$D_i(x,y) = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2} \tag{6}$$

3. Recalculation: recalculate the mean of all data points within each category, using the obtained mean as the new cluster centre for that category.
4. Iteration: repeat steps 2 and 3 until the cluster centres no longer change significantly or the preset number of iterations is reached. The preset number of iterations is 1000, and the preset threshold for cluster centre change is 0.01.

The within-cluster sum of squares (SSE) formula for K-means clustering is as follows:

$$SSE = \Sigma_{K=1}^{k} \Sigma_{X \in c_k} ||x - \mu_k||^2 \tag{7}$$

The clustering results are as follows, but considering the influence of the background colour of the image, $K=5$ is selected to retain 90% of the main colour information while avoiding the recommendation redundancy caused by excessive segmentation. In practical application, the height can be selected appropriately according to the extraction situation of the dominant colour (figure 4).

The K-means clustering method does not separate noise data, making it sensitive to the number of clusters and noise data. The number of clusters can be selected based on rules such as the elbow method. However, subjective parameter selection can result in significant differences in clustering results. Therefore, this paper defaults the number of clusters to 5,

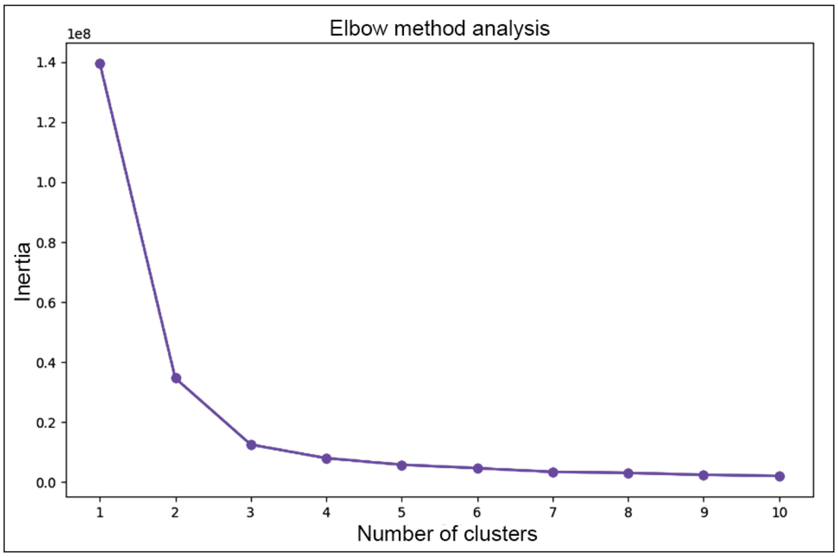

Fig. 4. SSE for cluster number selection

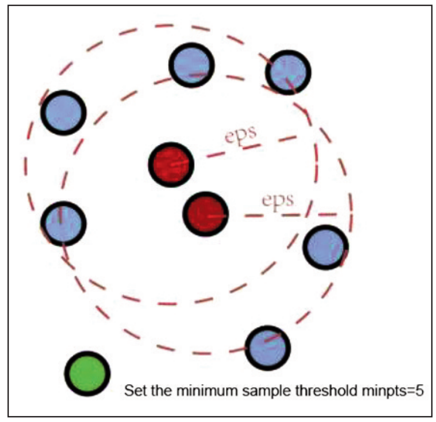

Fig. 5. Sample display example

assuming that the cluster centres of 5 clusters represent the five primary colours of the image.

DBSCAN clustering

DBSCAN (Density-Based Spatial Clustering of Applications with Noise) is a density-based spatial clustering algorithm that divides high-density regions into clusters based on the density differences inherent in the sample set. It defines clusters as the largest set of density-connected points. Unlike the K-means algorithm, which requires the user to specify the number of clusters, the DBSCAN algorithm achieves automatic clustering based on the density of data points under determined parameters, thus avoiding the influence of subjective cluster number selection on results and enabling the separation of noise data from the sample set. The core idea of DBSCAN is to divide the data points to be clustered into core points, edge points, and noise points based on the specified neighbourhood threshold ϵ and the minimum sample threshold *minPts*. The steps of the algorithm are as follows:

1. Initialisation: mark all points as unvisited.
2. Iteration: randomly select an unvisited point, calculate the distance from the other points to this point, and count the number of points within the neighbourhood threshold ϵ. If the number is greater than or equal to the minimum sample threshold *minPts*, the point is considered a core point, and a new cluster is created, with the point added to this cluster. If the number is less than the minimum sample threshold *minPts*, the point is considered a noise or edge point, and it is skipped, continuing to the next unprocessed data point.

As shown in the figure 5, if the number of points is greater than the set neighbourhood threshold ϵ, the point is marked as a red core point, while points within the neighbourhood threshold ϵ are marked as blue edge points. The above steps are repeated until all points have been traversed.

3. Formation of clusters: for each core point within a cluster, find all points within the neighbourhood threshold ϵ. If any of these points are unprocessed core points, add them to the cluster and continue searching for points within the neighbourhood threshold ϵ of these newly added points until no more core points can be added. If any of these points are edge points, add them to the cluster as well.
4. Determination of noise points: repeat steps (2) and (3) until all points have been processed. At this stage, any data points that have not been added to any cluster are considered noise points.

Through these steps, the data can be divided into different clusters, and noise data can be separated. In this algorithm, the choice of neighbourhood threshold ϵ and minimum sample threshold *minPts* parameters is crucial and needs to be determined through multiple trials or based on experience in the target domain.

In the parameter selection of the DBSCAN algorithm, this study fixed *minPts* as the empirical value range (5–15), and generated candidate parameter combinations in the eps $\in$ [0.1, 0.3] interval with a step size of 0.01. The initial value is set based on the data density distribution. For example, the data distribution of men's clothing is sparse, and the initial eps is 0.18. Young women's clothing is data-intensive with initial eps = 0.15. Then, the largest silhouette coefficient is selected to measure the closeness between the sample and its cluster and the separation between the sample and other clusters. The formula is as follows:

$$\bar{s} = \frac{1}{N}\sum_{i=1}^{N}\frac{b(i)-a(i)}{\max\{a(i),b(i)\}} \qquad (8)$$

where $a(i)$ is the average distance from the sample to other samples in the same cluster, and $b(i)$ – the average distance from the sample to the nearest different cluster sample. The contour coefficient and noise rate were used for manual verification, and the second derivative method was used to identify the critical point where the NR decline rate was significantly slowed down, and the parameters with a large contour coefficient were confirmed to confirm the rationality of the cluster structure.

Greedy algorithm

The core idea of the greedy algorithm is to break the entire problem into identical subproblems. First, make the optimal solution for the smallest subproblem based on the limited information available, and then gradually improve the information to obtain the optimal solution for the entire problem. After obtaining the clustering results from DBSCAN, this paper extracts the most representative *k* colours from each cluster of each brand, which are the most distinct primary colours. To find the most representative sample subset, this paper considers the *k* representative colours as a dynamically changing sample subset *T*. When the number of nodes in the dynamically changing sample subset reaches NUM, the iteration is performed based on the existing sample subset. The smallest Euclidean distance *Di* from the points in the remaining set NOT to the optimal sample subset is calculated, and the sample point with the largest minimum Euclidean distance is added to the optimal sample subset. The process is as follows:

1. Data grouping: group the data based on the clustering categories of each colour obtained from the DBSCAN algorithm.
2. Iterative step: initially, set the number of nodes in the dynamically changing sample subset NUM = 0, and select the first sample point to be added to the sample subset *T*. For each sample in the selected sample subset *T*, calculate the minimum distance between it and the unselected samples NOT, and select the sample that is “farthest” from *T* (i.e., the sample point in NOT with the largest minimum distance from *T*).
3. Repeat step (2): continue until *k* samples are selected or all samples have been considered.

RESULTS AND ANALYSIS

DBSCAN clustering results

The neighbourhood threshold ϵ defines the distance threshold within which data points are considered “close” to each other. A too large ϵ might lead to too many points being grouped into the same cluster, or even all points being classified into a single cluster, thus losing the local structural information of the data. Conversely, a too small ϵ might result in most points being considered as noise, leading to too many clusters or clusters with too few sample points. The minimum sample threshold *minPts* determines the minimum number of points required to form a cluster within a given neighbourhood. A higher *minPts* value can reduce the number of noise points, but also makes it harder to form clusters, possibly causing some small but meaningful clusters to be overlooked. Conversely, a lower *minPts* value might capture more small clusters but also introduce more noise points.

Therefore, selecting appropriate ϵ and *minPts* parameters is crucial for clustering effectiveness. The parameter tuning results, as shown in table 3, illustrate the outcomes of selecting these two core parameters and the corresponding noise rates for different clusters. This reflects the varying sensitivity of the algorithm to different data distribution characteristics and also reveals some of the internal structural features of the data.

For example, the colour clustering parameters for Lativ are ϵ = 0.154 and *minPts* = 10, with a noise rate of 13.77%. Similarly, for Peacebird Men, the parameters are ϵ = 0.152 and *minPts* = 10, with a noise rate of 13.36%, indicating that the density of data points within these two brands is comparable [16].

In contrast, although Elf Sack and H&M share the same colour clustering parameters (ϵ = 0.15 and *minPts* = 10), the noise rate for Elf Sack is 22.83%, which suggests a greater variability in data point density for Elf Sack compared to H&M. This contrast underscores the differing internal structures within the datasets for these brands, demonstrating how DBSCAN responds to the inherent characteristics of each data distribution.

In the results shown in table 3, the data points identified as noise by the DBSCAN algorithm, those that do not meet the criteria for forming clusters, often represent rare or non-mainstream colour choices in market applications. Although these colours have lower usage frequencies, they may symbolise innovation, uniqueness, or the preferences of specific target markets for brands. By analysing these noise data points as separate clusters, brands can understand which colour preferences are held by a small but loyal group of consumers [17]. This insight allows brands to design products or services that cater to this demographic or to use the colours found in the noise data as design inspiration to create novel and distinctive brand images or product lines that attract consumers seeking personalisation and differentiation.

Table 3

DBSCAN PARAMETER SELECTION

Brand	Brand		Noise rate (%)	Brand	Comparison brand		Noise rate (%)
	ϵ	*minPts*			ϵ	*minPts*	
Peacebird Women	0.17	10	10.96	Zara & Ochirly	0.165	12	14.86
Peacebird Men	0.152	10	13.36	Youngor & GXG	0.28	12	1.63
Peacebird Kids	0.15	10	16.61	Balabala & Annil	0.2	12	6.94
Ledin	0.154	10	13.77	Elf Sack & H&M	0.15	10	22.83

Therefore, although noise data in the DBSCAN algorithm is traditionally considered useless or data points that need to be excluded, in the context of market applications, it contains valuable information and potential significance. By appropriately adjusting the ϵ and *minPts* parameters in DBSCAN and fully leveraging both the clustered data and the noise data, brands can gain a more comprehensive understanding of market demand. This approach can help brands stand out in a highly competitive market and achieve differentiated development.

Greedy algorithm results

After obtaining the clustering results for each colour, this study aims to construct an optimal sample subset such that each subset can represent a cluster category. Based on the cluster to which each colour belongs, the first element from each cluster is initially selected to be included in the optimal sample subset. Then, the minimum Euclidean distance from the remaining data points to the points in the optimal sample subset is calculated. The data point with the maximum minimum Euclidean distance is then added to the optimal sample subset. The target number of samples in the subset is set to k = 10.

Using the strategy described above, a representative optimal sample subset can be constructed, which effectively reflects the main characteristics and distribution patterns of the colours in each cluster from the original dataset. This has significant practical implications for subsequent applications, such as visualisation analysis and market research.

Result output analysis

This paper aims to use an innovative and user-friendly approach to bridge the gap between consumers and brands regarding colour trends and applications through a carefully designed colour-selection website. This platform not only provides users with more ways to incorporate their preferences into fashion choices but also offers brands valuable insights into real-time changes in the consumer market. The website serves not only as a colour exploration platform but also as a tool for enhancing market insights and optimising brand strategies.

The homepage of the colour-selection website (figure 6) is designed to be simple yet visually appealing, striking a fine balance between aesthetic appeal and functional information delivery. The homepage offers clearly distinguished entry points for different types of users (general consumers and brands), guiding them quickly to the areas of content they are most interested in through intuitive icons and brief descriptions. This design approach not only enhances the user experience but also reflects a deep understanding of the needs of the target user groups. Additionally, the site includes sections for database sources and user suggestions, providing explanations about the sources of the public website data and creating a channel for real-time communication between developers and users.

Upon entering the consumer interface (figure 6), users can effortlessly select different clothing categories, such as women's wear, men's wear, children's wear, or accessories. As users make their selections, the interface dynamically displays the colour usage across various brands within the chosen category. Users can click on colours of interest or use filters to refine their preferences, allowing them to browse colour choices and clothing styles presented in the form of intuitive colour blocks and thumbnails. This makes the relationship between colours and clothing styles clear at a glance. When a user clicks on a specific colour, the page redirects to a detailed display of garments using that colour, complete with direct links to e-commerce platforms, fully satisfying both aesthetic and shopping needs.

After registering through the website or mobile terminal, users can fill in the basic information in the personal centre and select the initial colour preference (such as cold tone, high saturation, etc.) through the interactive colour tray. The system will dynamically update the preference model according to this information and the update of the e-commerce platform. Based on the DBSCAN clustering results and the 10 representative colours generated by the greedy algorithm, combined with the user's historical behaviour data, the clothing scheme that conforms to their aesthetic preferences will be recommended.

For brands, the colour-selection website serves as a powerful tool for market analysis and strategic planning. The brand interface (figure 7) focuses on analysis, offering precise matching and visual comparison of similar colour schemes between the brand's products and those of competitors in the market. This feature helps brands quickly identify their strengths and weaknesses in colour usage. Additionally, brand representatives can view product images from competing brands on e-commerce platforms and access direct links to sales data on platforms like Tmall and Taobao. This data provides robust support for refining market positioning, product optimisation, and marketing strategy adjustments.

Fig. 6. Homepage of the colour-selection website

Fig. 7. Consumer interface of the colour-selection website, colour comparison, and competitor

In addition, enterprises can view the category colour clustering results in real time, including the mainstream colour distribution, noise point characteristics and time series trends. At the same time, based on the clustering parameters and noise rate, enterprises can identify the market segments and adjust the product line design.
For example, limited edition colour series are launched for high noise rate categories. In terms of product promotion, companies can use colour sensitivity combined with geolocation data to deliver customised ads on social media platforms, such as high-brightness colour ads in tropical regions. High saturation of colour is often accompanied by decorative and symbolic performance, making the dress full of vitality [18].
For the prediction and verification of the fashion industry, users can carry out real-time trend capture and verification based on this platform. By continuously crawling the latest clothing data of the e-commerce platform, combined with DBSCAN clustering results, it can help experts verify the accuracy of fashion colour prediction. For example, if Pantone predicts that "mocamus" will become mainstream in 2025, the platform can provide empirical support by analysing the growth of searches for this colour in the young women's clothing category. Moreover, the platform supports the comparison and visualisation of multi-category colour distribution, and experts can quickly identify common trends, which provides a basis for cross-domain colour scheme design. The application can continue to expand to home furnishing, textile and other categories.
In summary, the colour-selection website is a powerful tool for market analysis and strategic planning. Brands can use it as a practical tool focused on colour comparison and competitor analysis, allowing them to precisely match and visually compare similar colour schemes between their products and those of competitors in the market. This helps brands quickly identify their strengths and weaknesses in colour usage and provides more timely references for observing market trends. Meanwhile, users can see it as a convenient platform for exploring fashion colours and discovering their preferred clothing.

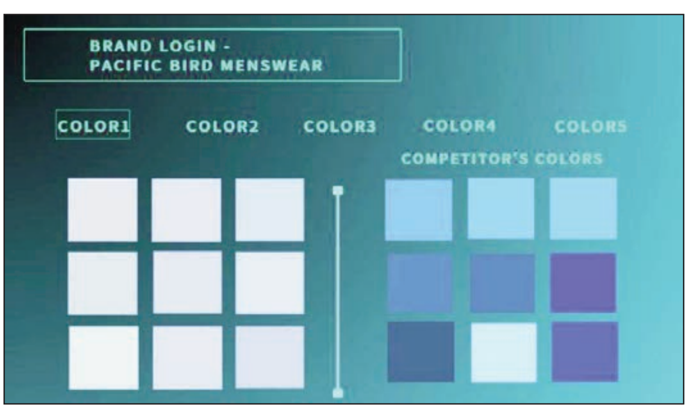

Fig. 8. Brand interface of the colour-selection website

CONCLUSION

At present, the model focuses on clothing colour analysis, but does not integrate the key design elements such as style cut, fabric texture and pattern. In future research, multi-scale Gabor filters can be introduced to extract fabric texture features (such as the gloss of silk and the roughness of wool), and the HSV colour space can be combined to construct cross-modal feature vectors. The attention mechanism (such as Transformer) is used to dynamically allocate weights to achieve collaborative recommendation of materials and colours. At the same time, the object detection technology can be introduced to segment the main body of the clothing and the background to improve the efficiency and accuracy of colour recognition.
In addition, we can continue to explore the possibility of market applications and design a reinforcement learning framework based on Deep Q-Network (DQN) to build a reward function with user behaviour sequences (click, like, purchase, return), so as to better realise market applications. Moreover, in the subsequent research, the cultural semantics and long-tail requirements of noise data in DBSCAN algorithm can be continued to be mined, and the BERT model can be used to analyse the semantic of clothing description texts (such as "Chinese style" and "Bohemian"), establish the "colour-cultural symbol" mapping relationship, and support the generation of colour scheme driven by cultural narrative.
For brands, the results of market colour analysis can not only inspire new product designs and accessory pairings but also provide deep insights into the evolution of colour trends in the present and near future. These insights can reveal which colours will lead the trends and which may gradually fade from view. Brands can leverage this information to cleverly incorporate popular colour elements into new designs and colour pairings, making their products not only functional but also visually appealing and emotionally resonant, thus increasing their market share. For example, by understanding that spring colour trends lean towards fresh and bright tones, a brand could design a vibrant and energetic spring clothing line or launch matching accessories to attract fashion-conscious and

individualistic consumers. They could also integrate their unique brand colours and elements into new designs, thereby better conveying and reinforcing the brand image.

For consumers, observing market colour trends enables a better understanding of the popular colours. By focusing on colour analysis results, consumers can sharply capture how seasonal changes, cultural shifts, and societal moods influence colour choices. This insight allows them to foresee which colours will become the latest trends, enabling them to make more forward-thinking shopping decisions. Whether purchasing clothing, home decor, or personal accessories, consumers can ensure that their choices are both in line with current aesthetic trends and reflective of their individuality. These insights can not only guide them in selecting products that suit them best but also help them maintain a unique style while following trends. This approach fosters a more rational view of trends, continuously enhancing their taste and aesthetic sensibilities.

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Credit risk-inclusive reverse factoring model for textile supply chains

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ABSTRACT – REZUMAT

Credit risk-inclusive reverse factoring model for textile supply chains

This paper investigates a two-tier supply chain comprising a core retailer and a capital-constrained supplier within the textile industry. Utilising the Stackelberg game model, the study examines three distinct scenarios for implementing reverse factoring: unsecured, third-party external guarantees, and platform-mediated factoring. The research incorporates the reputation loss risk faced by retailers in the textile sector and analyses the optimal strategies for reverse factoring financing under conditions of random market demand. The findings indicate that external guarantees do not significantly mitigate the adverse effects of reputation loss risk when core retailers proactively engage in reverse factoring financing. This suggests that the introduction of external guarantees in reverse factoring offers limited utility. Conversely, platform-mediated reverse factoring financing proves to be an effective mechanism for reducing the impact of reputation loss risk, with its efficacy increasing as the factoring company's credit line decreases. Furthermore, the study concludes that when the platform's service fee rate is low, textile retailers should opt for platform-mediated reverse factoring financing to optimise their financial operations.

Keywords: *reverse factoring, risk of reputation loss, guarantee, platform*

Model de factoring invers bazat pe riscul de credit pentru lanțurile de aprovizionare din sectorul textil

Prezenta lucrare analizează un lanț de aprovizionare pe două niveluri, format dintr-un retailer principal și un furnizor cu resurse financiare limitate din industria textilă. Folosind modelul jocului Stackelberg, studiul examinează trei scenarii distincte de implementare a factoringului invers: fără garanții, cu garanții externe din partea unor terți și factoring mediat de o platformă. Cercetarea a luat în considerare riscul de pierdere a reputației cu care se confruntă retailerii din sectorul textil și analizează strategiile optime de finanțare prin factoring invers în condiții de cerere aleatorie pe piață. Rezultatele indică faptul că garanțiile externe nu atenuează în mod semnificativ efectele negative ale riscului de pierdere a reputației atunci când comercianții cu amănuntul principali se angajează în mod proactiv în finanțarea prin factoring invers. Acest lucru sugerează că introducerea garanțiilor externe în factoringul invers oferă o utilitate limitată. În schimb, finanțarea prin factoring invers mediată de platformă se dovedește a fi un mecanism eficient pentru reducerea impactului riscului de pierdere a reputației, eficacitatea sa crescând pe măsură ce linia de credit a companiei de factoring scade. În plus, studiul concluzionează că atunci când rata comisioanelor de serviciu ale platformei este scăzută, comercianții cu amănuntul din sectorul textil ar trebui să opteze pentru finanțarea prin factoring invers mediată de platformă pentru a-și optimiza operațiunile financiare.

Cuvinte-cheie: *factoring invers, risc de afectare a reputației, garanție, platformă*

INTRODUCTION

The financing difficulties of SMEs in the textile industry have been a major factor restricting the development of the supply chain and the real economy, especially in the volatile business environment caused by factors such as the COVID-19 pandemic. More and more SMEs are facing growing financing needs. As one of the main ways to address the financing problems of SMEs in the textile industry, supply chain finance has attracted widespread attention in recent years [1–3]. Among these solutions, reverse factoring financing based on accounts receivable and initiated by the buyer's core enterprise provides a new financing model for SMEs in the textile industry that primarily use accounts receivable notes as the main financing method [4–6]. Unlike general factoring financing, in reverse factoring, banks, factoring companies, and other financial credit institutions no longer passively accept accounts receivable from SMEs in the textile industry. Instead, they actively evaluate and select core enterprises, transferring the financing risk from high-risk sellers to buyers with good credit [7]. Through direct evaluation and selection of core enterprises, the reliability of accounts receivable sources is guaranteed, and credit default risk is reduced [8]. Reverse factoring financing enables SMEs in the previously high-risk textile industry to obtain financing from financial institutions, effectively expanding the financing channels and efficiency of the textile industry, and has become a primary solution to the financing problems of SMEs with limited capital [9].

Due to its advantages, such as low financing risk and fast transaction processes, as well as the successful application of some reverse factoring platforms (such as Mexico's Nafin financing platform), reverse factoring has attracted significant attention from both domestic and international scholars. Research has primarily focused on two perspectives. The first is the motivation and value for core enterprises to engage in reverse factoring. Elliot et al. [10] explored the increasing use by banks of supply chain finance in the form of reverse factoring (RF) and its impact on overall value creation in supply chains. Li et al. [11] through investigations of 11 cases and interviews with 28 stakeholders from buyers, banks, and textile suppliers, pointed out that the number of textile suppliers, their dependence on buyers, and the cost difference between internal refinancing and reverse factoring are key factors affecting the development of reverse factoring financing. Tunca et al. [12] analysed the role and efficiency of buyer intermediaries in textile supplier financing by building a game theory model and found that financing strategies with buyer intermediaries can significantly improve channel performance and benefit all supply chain participants. Chen and Zhan [13] analysed three typical application models of reverse factoring in practice, discussing five aspects of the internal mechanisms of reverse factoring: operation mechanism, risk control, credit transfer, credit creation, and channel effects.

The second perspective concerns the intersection of reverse factoring and operations management. In the context of reverse factoring financing. Babich and Kouvelis [14] proposed a research framework on the interaction between finance, operations, and risk management, highlighting the impact of reverse factoring on supply chain performance as a prevalent research topic. Van Der Vliet et al. [15] argued that the size of the payment term extension that a supplier can accommodate depends on demand uncertainty and the cost structure of the supplier. Wu et al. [16] compared the effects of three supply chain finance schemes, advance payment, delayed payment, and reverse factoring, on the financial performance of textile suppliers and retailers, indicating that when textile suppliers have financing advantages, delayed payment benefits both suppliers and retailers. When retailers have financing advantages, advance payment and reverse factoring are better options for both. Other studies compare reverse factoring with other supply chain financing strategies. For example, Gelsomino et al. [17] compared reverse factoring, inventory financing, and dynamic discounts, three financing methods with buyer involvement in core enterprises, and discussed their impact on buyer benefits, emphasising the importance of working capital demand and financial costs in evaluating financing schemes. Zhu and Ou [18] proposed a three-level Stackelberg game model in the reverse factoring financing scenario, internalising bank interest rates for the first time and comparing reverse factoring with traditional commercial loans and forward factoring financing, showing that reverse factoring can effectively resolve fraud issues. Kouvelis and Xu [19] compared forward and reverse factoring financing from a credit rating perspective, noting that reverse factoring can take advantage of the payment guarantees from textile retailers and the credit rating differences between small suppliers and large retailers, enabling suppliers to obtain financing at more favourable interest rates. This literature further suggests that optimised reverse factoring schemes can increase the profits of textile retailers, and even if retailers lack credit advantages, reverse factoring financing strategies can still help resolve the financing issues of upstream suppliers. The emergence and application of reverse factoring makes the risk of supply chain financing change from high risk for small and medium-sized enterprises to low risk for core enterprises. However, at the same time, as a core enterprise that initiates reverse factoring financing, the core enterprise's commercial credit to upstream textile suppliers is transformed into bank credit to financial credit institutions as the object of payment for the goods receivable changes from textile suppliers to banks, factoring companies and other financial credit institutions after the accounts receivable maturity. As a result, core enterprises are often faced with problems such as declining market sales and increasing pressure of capital withdrawal caused by reputation problems, such as product quality of textile suppliers in reverse factoring, and thus bear the risk of reputation loss. Hu et al. [20] analysed supply chain cooperation in reverse factoring financing and robust decision-making under demand disturbance under the premise of considering the risk of reputation loss of core enterprises, and discussed the reasons why core enterprises are still willing to take the initiative to carry out reverse factoring in the face of reputation loss risk. However, it should be pointed out that there is little literature on how to avoid the core enterprise reputation risk in reverse factoring, especially the optimal development strategy of reverse factoring considering the core enterprise reputation loss risk. Based on this, this part takes the two-level supply chain consisting of a textile retailer in a core-enterprise position and a textile supplier with limited capital as the research object. In view of the reputation loss risk faced by textile retailers in reverse factoring, the optimal strategy for textile retailers to carry out reverse factoring is discussed by considering the introduction of a guarantee or the use of a platform. Compared to existing literature, this study complements Liebl et al. (2016) by explaining why guarantees fail in reverse factoring and extends Babich's (2018) framework by quantifying the interaction between reputation risk and platform service fees.

PROBLEM DESCRIPTION AND BASIC FRAMEWORK

Problem description

The research problem addressed in this paper concerns a two-tier supply chain comprising a core retailer and a capital-constrained supplier. The retailer purchases a single product from the supplier at a predetermined wholesale price, sells it in a variable market, and delays payment, resulting in accounts receivable. Due to capital constraints, the supplier is unable to meet optimal order quantities and faces difficulties in obtaining credit from financial institutions because of its limited size and low credit rating. In contrast, the retailer, as the core enterprise, can secure low-cost financing from financial institutions due to its strong credit rating. To help overcome financing constraints faced by upstream suppliers, retailers consider two reverse factoring strategies: proactively entering into agreements with banks or utilising supply chain management platforms (e.g., the Nafin platform in Mexico). In the proactive strategy, the retailer mitigates the risk of credibility loss by obtaining unsecured and partial credit guarantees from a third-party agency. In contrast, the supply chain management platform strategy focuses on the potential for financing facilitated through the platform. The flowcharts of financing decisions under different reverse factoring scenarios are shown in figures 1 and 2, respectively.

In reverse factoring, the supplier first sets the wholesale price, after which the retailer decides the order quantity and delays payment, creating accounts receivable. To maintain optimal supply chain performance, the core retailer plans to address the funding constraints of upstream suppliers through reverse factoring. As illustrated in figure 1, the retailer initiates the reverse factoring process by partnering with a bank. The retailer agrees to assign its suppliers' accounts receivable and negotiates the bank's credit limit and interest rate. Subsequently, suppliers with limited funds apply for financing from the bank using their accounts receivable notes. The bank verifies the authenticity of the notes and provides the credit. At maturity, the retailer repays the bank, which collects the payment based on the agreed credit limit. Ultimately, the retailer settles the payment with the bank, which then compensates the supplier according to the agreed credit terms. The retailer may also involve a third-party guarantor to ensure the credibility of the financing.

As shown in figure 2, a platform-assisted reverse factoring strategy connects the core retailer, the capital-constrained supplier, and the bank. Once the supplier provides the accounts receivable, the retailer confirms the bill on the platform. The platform then auctions the factored accounts receivable, selects a bank, and determines the factoring amount based on the bidding results. At this stage, the bank becomes the creditor of the accounts receivable and provides credit to the supplier. The retailer then repays the bank directly when due. Throughout the financing process, the supply chain management platform charges a handling fee, which is based on the bank's granted credit.

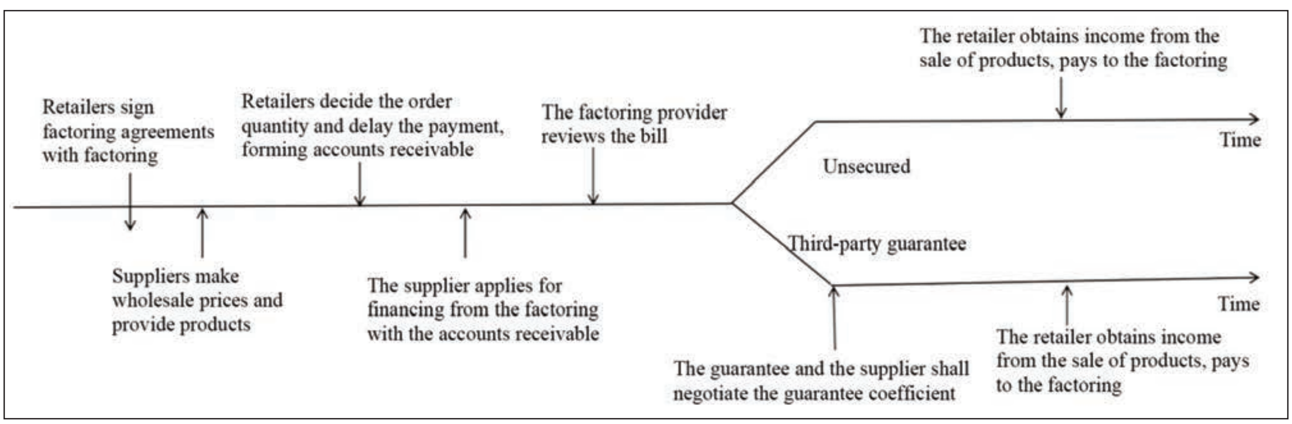


Fig. 1. Decision-making flowchart for retailer-initiated factoring strategy

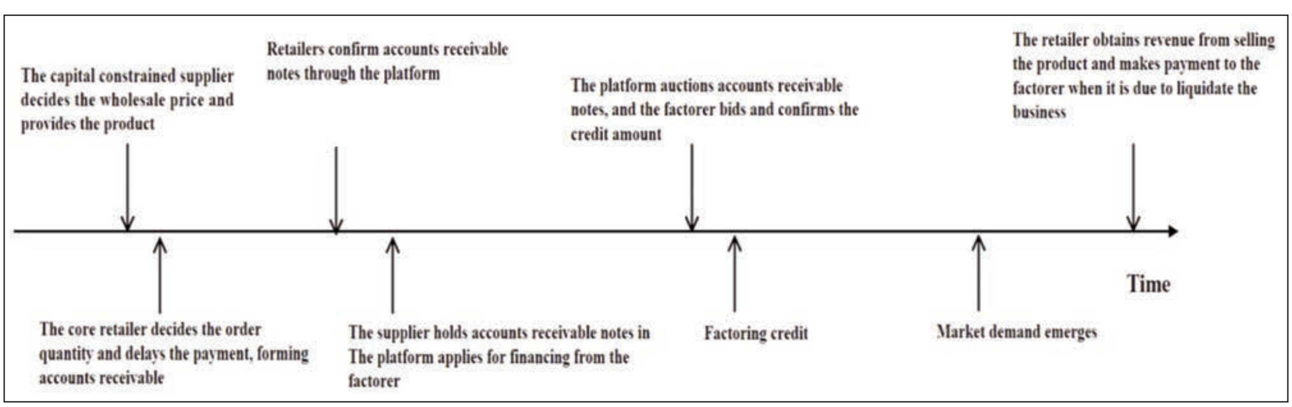


Fig. 2. Decision-making process framework for supply chain financing intermediation through reverse factoring platforms

Table 1

PARAMETERS AND VARIABLES	
Parameters	**Decision variables**
p: Retailer's market selling price per unit of product	w: supplier's wholesale price
c: The supplier's production cost per unit of product	q: Retailer's order quantity
l: Coefficient to measure the risk of loss of creditworthiness of the retailer	Function:
A: Credit lines granted by banks to core businesses (retailers)	Π: Profit function for each participant in financing
r: The bank's credit rate (generally a fixed value above the bank's interest rate)	R: Retailer; Supplier
ξ: The service fee rate of the supply chain management platform	SC: The overall supply chain (Supply Chain)
λ: The guarantee coefficient of the external third-party guarantee institution	1,2,3: Represent the active reverse factoring strategy under an unsecured and third-party external guarantee, and the reverse factoring strategy under a supply chain management platform facilitated financing, respectively.
β: Guarantee rate of external third-party guarantee institutions for unit financing	
D: Demand in the retail market	
f(D), F(D): probability density function of random market demand, cumulative distribution function	

Description of symbols and model assumptions

The symbols and descriptions used in this paper are shown in table 1 below.
The basic Model Assumptions of this paper are as follows:
(1) All participants in the financing business are risk-neutral and possess symmetric information.
(2) The retailer orders in a single period and faces random market demand with a probability density function $f(D)$ and cumulative distribution function $F(D)$, and it satisfies the generalised increasing failure rate (Increasing Generalised Failure Rate, IGFR), $H(D) = \frac{Df(D)}{1-F(D)}$ which represents the generalised increasing failure rate.
(3) The initial capital of the capital-constrained supplier is assumed to be zero.
(4) At the end of the sales period, the retailer's out-of-stock costs and the salvage value of unsold products are assumed to be zero.

CREDIT RISK-EMBEDDED REVERSE FACTORING FINANCING MODEL

Benchmark model: no guarantee

The decision flow diagram for this scenario is presented in figure 1. First, the capital-constrained supplier determines its wholesale price by solving the optimisation problem presented in equation 1 below.

$$\max_{w_1} \Pi_1^S(w_1) = w_1 q_1 - cq_1(1+r) \quad (1)$$

Second, the retailer decides the order quantity and delays payment, which can be formulated as the optimisation problem shown in equation 2 below:

$$\max_{q_1} \Pi_1^R(q_1) = pE_D \min\{D, q_1\} - w_1 q_1 - \frac{cq_1}{A} l \quad (2)$$

The problems in equations 1 and 2 represent a typical Stackelberg game, solved using the inverse order method to derive the optimal solution presented in Lemma 1.
Lemma 1: In unsecured active reverse factoring, the optimal decisions for each financing participant are:
(1) The supplier's optimal wholesale price w_1^* satisfies the equation: $w_1^* = p\bar{F}(q_1^*) - \frac{cl}{A}$;
(2) The retailer's optimal order quantity q_1^* satisfies the equation:

$$p\bar{F}(q_1^*)\left(1 - H(q_1^*)\right) = c\left(1 + r + \frac{l}{A}\right)$$

Proof: Differentiate equation 2 with respect to q_1, let $\frac{d\Pi_1^R}{dq_1} = p\bar{F}(q_1) - w_1 - \frac{cl}{A} = 0$, we get: $w_1 = p\bar{F}(q_1) - \frac{cl}{A}$. Substitute it back into equation 1, continue to differentiate with respect to q_1, let

$$\frac{d\Pi_1^S}{dq_1} = p\bar{F}(q_1)\left(1 - H(q_1)\right) - c\left(1 + r + \frac{l}{A}\right) = 0,$$

and solve the system of equations to prove Lemma 1.
Lemma 1 indicates that the factor's credit line, financing rate, and the retailer's credit loss risk significantly influence the optimal decisions of stakeholders, as formalised in Proposition 1.
Proposition 1: In unsecured active reverse factoring, three key factors are: $w_1^* \propto r$, $q_1^* \propto \frac{1}{r}$, $q_1^* \propto A$, and $q_1^* \propto \frac{1}{l}$; in addition, there are two further factors: $\Pi_1^R \propto \frac{1}{r}$, $\Pi_1^R \propto A$, and $\Pi_1^R \propto \frac{1}{l}$, where the symbol '$\propto$' denotes a positive relationship.
Proof: Based on the optimal solutions derived in Lemma 1 and the Increasing Generalised Failure Rate (IGFR) property, we conclude $q_1^* \propto \frac{1}{r}$, $q_1^* \propto \frac{1}{l}$, $q_1^* \propto A$, $w_1^* \propto r$. Simplifying equation 2, we obtain

$\prod_1^R = pE_D \min\{D, q_1^*\} - pq_1^* \bar{F}(q_1^*)$, and setting $K(x) = pE_D \min\{D, x\} - px\bar{F}(x)$, we derive $\frac{dK(x)}{dx} = pxf(x) > 0$. Thus, $\prod_1^R \propto q_1^*$, $\prod_1^R \propto A$, $\prod_1^R \propto \frac{1}{l}$.

Proposition 1 highlights two key findings. First, an increase in the financing rate raises the supplier's wholesale price while reducing the retailer's order quantity and profit. This occurs because higher financing costs compel the supplier to increase wholesale prices, which subsequently suppresses the retailer's ordering incentive. Second, the retailer's order quantity and profit increase with the factor's credit line but decrease with the credit loss coefficient. A higher credit loss risk exacerbates market demand volatility and liquidity pressure, dampening the retailer's operational flexibility. Conversely, a larger credit line mitigates the adverse effects of credit risk, fostering higher order quantities and profitability.

Reverse factoring financing model with a third-party external guarantee

As indicated by Proposition 1, the credit loss risk borne by the retailer significantly undermines their incentive to actively engage in reverse factoring without guarantees. To mitigate this impact, therefore, the introduction of third-party agencies to guarantee financing for businesses is considered to reduce the impact of reputation loss risk on retailers.

The decision flowchart with a third-party external guarantee is shown in figure 1.

$$\max_{w_2} \prod_2^S(w_2) = w_2q_2 - cq_2(1 + r) - \beta cq_2 \qquad (3)$$

Second, the retailer's decision on order quantity and payment delay can be formulated as an optimisation problem, as shown in equation 4 below:

$$\max_{q_2} \prod_2^R(q_2) = pE_D \min\{D, q_2\} - w_2q_2 - \frac{cq_2}{A}l + \lambda\frac{cq_2}{A}l \qquad (4)$$

The supplier then reaches an agreement with the external third-party guarantor on the guarantee coefficients and rates.

This is expressed as a solution to the problem in equation 5 below:

$$\beta cq_2 = \lambda\frac{cq_2}{A}l \qquad (5)$$

Similarly, the problem in equations 3 to 5 is a typical Stackelberg game. It can be solved using the reverse order method to find the optimal solution, as shown in Lemma 2.

Lemma 2: In reverse factoring involving a third-party external guarantor, the optimal decisions of financing participants are as follows:

(1) The optimal wholesale price w_2^* for the supplier is given by the following equation:

$$w_2^* = p\bar{F}(q_2^*) - (1 - \lambda)\frac{cl}{A}.$$

(2) The optimal order quantity q_2^* for the retailer is given by the following equation:

$$p\bar{F}(q_2^*)\left(1 - H(q_2^*)\right) = c\left(1 + r + \frac{l}{A}\right).$$

(3) The guarantee rate and guarantee coefficient of the external third-party guarantee institution are given by the following: $\beta = \frac{\lambda l}{A}$.

Proof: From Eq. (5), it is evident that $\beta = \frac{\lambda l}{A}$. Taking the derivative of equation 4 with respect to q_2 and setting $\frac{d\prod_2^R}{dq_2} = p\bar{F}(q_2) - w_2 - \frac{cl}{A} + \lambda\frac{cl}{A} = 0$, we obtain $w_2 = p\bar{F}(q_2) - (1 - \lambda)\frac{cl}{A}$.

Substituting this into equation 3, taking the derivative with respect to q_2, and setting

$$\frac{d\prod_2^S}{dq_2} = p\bar{F}(q_2)\left(1 - H(q_2)\right) - c\left(1 + r + \frac{l}{A}\right) = 0,$$

By solving these equations simultaneously, we thereby prove Lemma 2.

Similar to Lemma 1, Lemma 2 states that when an external third-party guarantor is introduced for reverse factoring, the bank's credit limit and rate for the core retailer, the retailer's risk of creditworthiness loss, and the guarantor's coefficient significantly impact each participant's optimal decision-making, as shown in Proposition 2.

Proposition 2: In the case of reverse factoring with partial credit guarantee from a third-party external guarantor, the following relationships hold: $w_2^* \propto r$, $q_2^* \propto \frac{1}{r}$, $w_2^* \propto \lambda$, $q_2^* \perp \lambda$, and $q_2^* \propto A$, $q_2^* \propto \frac{1}{l}$. Furthermore, $\prod_2^R \propto \frac{1}{r}$, $\prod_2^R \propto A$, $\prod_2^R \propto \frac{1}{l}$, but $\prod_2^R \perp \lambda$, $\prod_2^S \perp \lambda$. Here, the symbol $\propto$ denotes a proportional relationship and $\perp$ indicates that the two variables are unrelated.

Proof: Based on the optimal solutions derived from Lemma 2 and the proof of Proposition 1, it is evident that $w_2^* \propto r$, $q_2^* \propto \frac{1}{r}$, $w_2^* \propto \lambda$, $q_2^* \perp \lambda$, $q_2^* \propto A$, $q_2^* \propto \frac{1}{l}$, $\prod_2^R \propto \frac{1}{r}$, $\prod_2^R \propto A$, $\prod_2^R \propto \frac{1}{l}$, $\prod_2^S \perp \lambda$. Since

$$\prod_2^S = pq_2^*\bar{F}(q_2^*) - cq_2^*\left(1 + r + \frac{l}{A}\right), \text{ and } q_2^* \perp \lambda,$$

it follows that $\prod_2^S \perp \lambda$.

Proposition 2 presents the following conclusions. First, similar to Proposition 1, the supplier's optimal wholesale price increases with the reverse factoring interest rate, while the retailer's optimal order quantity and its own profit decrease with the reverse factoring interest rate. Additionally, the retailer's order quantity and optimal profit increase with the factor's credit line and decrease with the credit loss risk coefficient, for reasons consistent with those explained in Proposition 1.

Second, it is noteworthy that Proposition 2 indicates that even when a third-party external guarantor is introduced to provide a partial credit guarantee to mitigate the retailer's credit loss risk, the retailer's optimal decisions and profits remain unaffected by changes in the guarantee coefficient. This is because the guarantee fee is borne by the supplier, which increases the supplier's financing costs and consequently leads to a higher wholesale price. This higher wholesale price offsets the positive effect of the guarantee in reducing the retailer's credit loss risk. Although the retailer benefits from a reduced credit loss risk through the guarantee, it faces a higher wholesale price, ultimately resulting in no change in the optimal order quantity. Moreover, the increase in ordering costs is offset by the reduction in credit loss risk, leaving the retailer's optimal profit unchanged.

Proposition 2 leads to the following conclusions: First, similar to Proposition 1, the supplier's wholesale price increases with a higher factoring rate, while the retailer's order quantity and optimal profit decrease. Additionally, the retailer's order quantity and optimal profit increase with the bank credit limit and decrease with the creditworthiness loss coefficient, as explained in Proposition 1.

Second, Proposition 2 highlights that despite introducing a third-party guarantor to partially guarantee the financing and reduce the retailer's creditworthiness risk, the guarantee coefficient does not affect the retailer's optimal decision or profit. This is because the supplier bears the financial burden of the guarantee. The supplier's financing costs increase due to the guarantee, leading to higher wholesale prices. This cancels out the positive effect of the guarantee in reducing the retailer's reputational risk. The reduction in reputational risk is offset by the higher wholesale price, leading to a constant optimal order quantity and increased ordering costs. However, the constant optimal profit is maintained due to the reduction in reputational risk.

Based on the preceding lemmas and propositions, Proposition 3 is derived through a comparative analysis of Propositions 1 and 2.

Proposition 3: In the active reverse factoring financing model, the following relationships hold: $w_1^* < w_2^*$, $q_1^* = q_2^*$, but $\Pi_1^S = \Pi_2^S$, $\Pi_1^R = \Pi_2^R$, $\Pi_1^S + \Pi_1^R = \Pi_1^{SC} = \Pi_2^{SC} = \Pi_2^S + \Pi_2^R$.

Proof: According to Lemma 1 and Lemma 2, it is evident that $q_1^* = q_2^*$, and thus

$$w_1^* = p\bar{F}(q_1^*) - \frac{cI}{A} < p\bar{F}(q_1^*) - (1-\lambda)\frac{cI}{A} = w_2^*.$$

By simplifying the profit functions

$$\Pi_1^S = pq_1^*\bar{F}(q_1^*) - cq_1^*\left(1 + r + \frac{I}{A}\right),$$

$$\Pi_1^R = pE_D \min\{D, q_1^*\} - pq_1^*\bar{F}(q_1^*),$$

$$\Pi_2^S = pq_2^*\bar{F}(q_2^*) - cq_2^*\left(1 + r + \frac{I}{A}\right),$$

$$\Pi_2^R = pE_D \min\{D, q_2^*\} - pq_2^*\bar{F}(q_2^*),$$

we have $\Pi_1^R = \Pi_2^R$, $\Pi_1^S + \Pi_1^R = \Pi_1^{SC} = \Pi_2^{SC} = \Pi_2^S + \Pi_2^S$.

Proposition 3 illustrates that in the reverse factoring financing model, the introduction of a third-party guarantee does not increase the profits of either the retailer or the overall supply chain. Furthermore, Proposition 3 indicates that the introduction of a third-party guarantee leads to an increase in the supplier's wholesale price, without enhancing the supplier's profit. Therefore, Proposition 3 concludes that in the context of supply chain accounts receivable reverse factoring financing, if the core enterprise actively provides reverse factoring to capital-constrained small and medium-sized enterprises, the partial credit guarantee provided by a third-party external guarantor cannot effectively mitigate the credit loss risk borne by the core enterprise in the financing process. Additionally, the supplier's assumption of the guarantee fee forces the supplier to increase the wholesale price. Although the introduction of the guarantee maintains the operational efficiency of all participating entities and the supply chain, there are many hidden costs in supply chain operations, such as labour and time. Therefore, in the active reverse factoring financing model, it is not advisable to mitigate the credit loss risk by introducing a third-party external guarantor, or if such a method is adopted, the capital-constrained small and medium-sized enterprises should not bear the guarantee fee.

Platform-mediated reverse factoring financing model

The decision flowchart for this scenario is shown in figure 2. First, the capital-constrained supplier decides the wholesale price w_3, which can be expressed as solving the optimisation problem shown in equation 6.

$$\max_{w_3} \Pi_3^S(w_3) = w_3q_3 - cq_3(1 + r) \tag{6}$$

Second, the retailer decides the order quantity with delayed payment. In this scenario, the platform acts as an intermediary and charges a certain percentage of the financing service fee, but also transfers the retailer's credit loss risk to the factoring platform. The retailer's decision can be expressed as solving the optimisation problem shown in equation 7.

$$\max_{q_3} \Pi_3^R(q_3) = pE_D \min\{D, q_3\} - w_3q_3 - \xi cq_3 \tag{7}$$

Similarly, equations 6 and 7 represent a typical Stackelberg game problem, which is solved using backward induction, with the optimal solution shown in Lemma 3.

Lemma 3: In platform-mediated reverse factoring, the optimal decisions of the financing participants are as follows:

The supplier's optimal wholesale price w_3^*:

$$w_3^* = p\bar{F}(q_3^*) - \xi c.$$

The retailer's optimal order quantity q_3^*:

$$p\bar{F}(q_3^*)\left(1 - H(q_3^*)\right) = c(1 + r + \xi).$$

Proof: Differentiating equation 7 with respect to q_3, setting $\frac{d\Pi_3^R}{dq_3} = p\bar{F}(q_3) - w_3 - \xi c = 0$, yields $w_3 = p\bar{F}(q_3) - \xi c$. Substituting this into equation 6 and differentiating with respect to q_3, setting

$$\frac{d\Pi_3^S}{dq_3} = p\bar{F}(q_3)\left(1 - H(q_3)\right) - c(1 + r + \xi) = 0,$$

Lemma 3 is proved by combining these results.

Lemma 3 shows that by leveraging the reverse factoring platform, the core retailer transfers its credit loss risk in the financing process to the reverse factoring platform by paying a certain service fee, making the decisions of the supply chain participants independent of the credit loss risk. Similarly, the analysis of the optimal solution in Lemma 3 leads to Proposition 4.

Proposition 4: In platform-mediated reverse factoring, the following relationships hold: $w_3^* \propto r$, $q_3^* \propto \frac{1}{r}$, $q_3^* \propto \frac{1}{\xi}$. Additionally, $\Pi_3^R \propto \frac{1}{r}$, $\Pi_3^R \propto \frac{1}{\xi}$, where the symbol $\propto$ denotes a proportional relationship.

Proof: Based on Lemma 3, $w_3^* = p\bar{F}(q_3^*) - \xi c$, and q_3^* satisfies $p\bar{F}(q_3^*)(1 - H(q_3^*)) = c(1 + r + \xi)$. Similarly, since $p\bar{F}(q_3^*)(1 - H(q_3^*)) \propto \frac{1}{q_3^*}$. It follows that $q_3^* \propto \frac{1}{r}$, $q_3^* \propto \frac{1}{\xi}$, $w_3^* \propto r$. Substituting the optimal solution, $\Pi_3^R = pE_D \min\{D, q_3^*\} - pq_3^*\bar{F}(q_3^*)$, and similar to the proof of Proposition 1, $\Pi_3^R \propto \frac{1}{r}$, $\Pi_3^R \propto \frac{1}{\xi}$.

Unlike the conclusions presented in Propositions 1 and 2, Proposition 4 indicates that platform-mediated financing can effectively mitigate the credit loss risk borne by the retailer in the financing process, making the decisions of the supplier and retailer independent of the credit loss risk coefficient. However, since the platform charges a certain percentage of the service fee based on the financing amount, the retailer's order quantity decreases, ultimately leading to a decrease in the retailer's optimal profit as the platform's service fee rate increases.

OPTIMAL STRATEGY ANALYSIS FOR REVERSE FACTORING FINANCING

Model analysis

From the optimal solutions shown in Lemma 1 to Lemma 3 above and the analyses of Proposition 1 to Proposition 4, Proposition 5 can be obtained as follows.

Proposition 5: In reverse factoring considering the retailer's credit loss risk, if $0 < \xi < \hat{\xi}$, then $q_1^* = q_2^* < q_3^*$, $\Pi_1^R = \Pi_2^R < \Pi_3^R$.

Conversely, if $\hat{\xi} < \xi < 1$, then $q_1^* = q_2^* > q_3^*$, $\Pi_1^R = \Pi_2^R > \Pi_3^R$, where $\hat{\xi} = \frac{l}{A}$, and it is evident that $\hat{\xi} \propto 1$, $\hat{\xi} \propto \frac{1}{A}$.

Proof: Based on the optimal solutions derived from Lemmas 1, 2, and 3, we have:

In the no-guarantee scenario: $w_1^* = p\bar{F}(q_1^*) - \frac{cl}{A}$, q_1^* satisfies $p\bar{F}(q_1^*)(1 - H(q_1^*)) = c(1 + r + \frac{l}{A})$.

In the third-party guarantee scenario: $w_2^* = p\bar{F}(q_2^*) - (1-\lambda)\frac{cl}{A}$, q_2^* satisfies $p\bar{F}(q_2^*)(1 - H(q_2^*)) = c(1 + r + \frac{l}{A})$.

In the platform-mediated scenario: $w_3^* = p\bar{F}(q_3^*) - \xi c$, q_3^* satisfies $p\bar{F}(q_3^*)(1 - H(q_3^*)) = c(1 + r + \xi)$.

Thus, it is evident that $q_1^* = q_2^*$, and $w_1^* < w_2^*$. Since $\bar{F}(q)(1 - H(q)) \propto \frac{1}{q}$, if $\xi < \hat{\xi} = \frac{l}{A}$, then $q_3^* > q_1^* = q_2^*$.

Conversely, if $\hat{\xi} < \xi < 1$, then $q_1^* = q_2^* > q_3^*$. Since:

$$\Pi_1^S = pq_1^*\bar{F}(q_1^*) - cq_1^*(1 + r + \frac{l}{A}),$$

$$\Pi_1^R = pE_D \min\{D, q_1^*\} - pq_1^*\bar{F}(q_1^*).$$

$$\Pi_2^S = pq_2^*\bar{F}(q_2^*) - cq_2^*(1 + r + \frac{l}{A}),$$

$$\Pi_2^R = pE_D \min\{D, q_2^*\} - pq_2^*\bar{F}(q_2^*).$$

$$\Pi_3^S = pq_3^*\bar{F}(q_3^*) - cq_3^*(1 + r + \xi),$$

$$\Pi_3^R = pE_D \min\{D, q_3^*\} - pq_3^*\bar{F}(q_3^*).$$

when $0 < \xi < \hat{\xi} = \frac{l}{A}$, $\Pi_1^R = \Pi_2^R < \Pi_3^R$, conversely, $\Pi_1^R = \Pi_2^R > \Pi_3^R$.

Proposition 5 presents the following conclusions. Firstly, in the reverse factoring financing model that accounts for the retailer's (the core enterprise's) credit loss risk, the retailer's order quantity via the platform for reverse factoring financing increases when the service fee rate charged by the platform for facilitating transactions between the retailer and the supplier is low. This low fee incentivises the retailer to utilise the platform for reverse factoring financing. Conversely, when the platform's service fee rate is high, the retailer tends to engage directly in reverse factoring financing; however, this approach does not alleviate the impact of credit loss risk on financing efficiency, even with the introduction of external guarantees. This is due to the fact that platform-facilitated financing effectively reduces the negative effects of credit loss risks on the operational and financial efficiency of various entities within the supply chain. A relatively low service fee rate for platform-facilitated financing can significantly enhance the retailer's willingness to place orders, subsequently increasing their profits, and vice versa.

Secondly, as the retailer's credit loss risk escalates or the factoring company's credit limit diminishes, retailers are increasingly inclined to pursue reverse factoring financing through the platform. The analysis indicates that heightened reputational loss risk drives retailers to favour platform-mediated reverse factoring financing. Furthermore, a decrease in the credit line offered by the factoring company leads to an increase in the supplier's unit financing amount, which indirectly intensifies the adverse effects of reputational loss risk on the retailer's profits. Consequently, this shift in the retailer's strategy towards platform-mediated financing reflects a willingness to accept higher service fees in order to mitigate the negative impacts of reputational loss risk.

Proposition 5 outlines the optimal strategy for core enterprises to engage in reverse factoring while considering the potential risk of reputational loss. It also clarifies why core enterprises rarely introduce guarantees to facilitate reverse factoring financing. Additionally, it highlights that guarantee institutions should not prioritise collaboration with core enterprises in reverse factoring financing. For reverse factoring platforms, if the factoring institution's credit line to the core enterprise is significant or if the risk of reputational loss for the core enterprise is minimal, the platform should consider reducing the service fee rate charged for facilitating financing. This approach can effectively broaden the platform's client base.

Managerial implications of platform fee rate optimisation

From a policy perspective, governments and industry regulators should establish a dynamic guidance mechanism for platform service fees to balance the interests of all stakeholders. Specifically, when factoring companies have low credit lines or retailers face high reputation loss risks, regulators could provide subsidies to reverse factoring platforms to offset part of their service costs, enabling platforms to lower the fee rate below the threshold. This policy intervention would encourage more retailers to adopt platform-mediated financing, thereby alleviating financing constraints for suppliers in the textile industry. Additionally, regulators should mandate transparency in platform fee structures, requiring platforms to disclose how fees are calculated relative to risk transfer (e.g., the ratio of fees to reputation loss risk mitigation), which helps suppliers make informed financing decisions.

For suppliers, the key is to leverage platform-mediated financing when the service fee rate is low. Since platform financing decouples its wholesale pricing from retailers' reputation risk (Proposition 4), suppliers can avoid increasing wholesale prices to cover guarantee costs (unlike the third-party guarantee scenario). To further reduce costs, suppliers could form alliances to negotiate with platforms for group-based fee discounts. Larger transaction volumes from alliances can give suppliers more bargaining power to lower prices, thereby increasing their profit margins. Moreover, suppliers should prioritise platforms that offer flexible fee adjustments based on transaction history; for example, platforms that reduce fees for long-term, low-default clients can help suppliers build sustainable financing relationships.

Numerical analysis

First, a numerical analysis is conducted for the reverse factoring financing models under the scenarios of no guarantee and partial credit guarantee by a third-party external guarantor, as shown in Example 1.

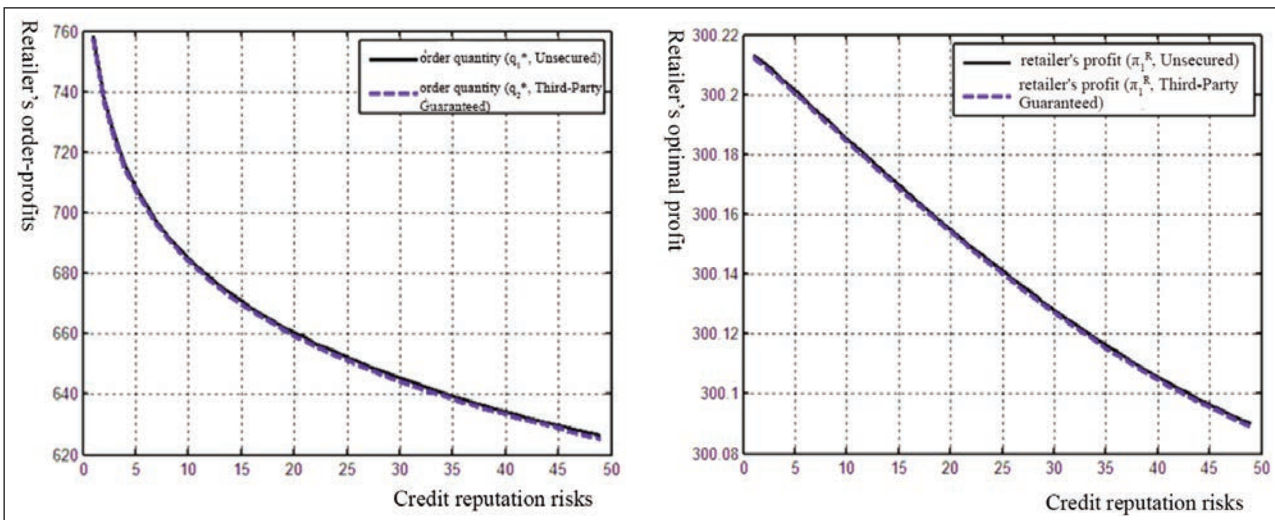
Example 1: Assume that the retailer's market demand for the product follows a normal distribution with a mean of 1000 and a variance of 300. The unit price of the product is $p = 1$. The capital-constrained supplier has an internal capital level of 0, and the unit production cost of the product is $c = 0.2$. The factoring company's credit line is $A = 3000$, and the credit interest rate is $r = 0.1$.

(1) The guarantee coefficient in the case of external guarantee is $\lambda = 0.2$. The retailer's optimal decisions and profits as a function of the credit loss risk are shown in figure 3.

(2) The retailer's credit loss risk coefficient is $l = 30$. The optimal decisions and profits of the supplier and retailer as a function of the guarantee coefficient are shown in figures 4 and 5, respectively.

From figures 3 to 5, it can be observed that, consistent with Propositions 1 to 3, regardless of whether there is an external guarantee, the retailer's order quantity and optimal profit decrease as the credit loss risk increases (figure 3). Additionally, in the case of a third-party external guarantee, the supplier's wholesale price increases with the guarantee coefficient (figure 4, *a*), but the retailer's order quantity (figure 4, *b*) and the profits of all parties (figure 5) do not change with the guarantee coefficient. Compared to the no-guarantee scenario, the supplier's wholesale price is higher in the third-party external guarantee scenario (figure 4, *a*), and the profits of the financing participants and the overall supply chain do not improve (figure 5).

Next, a numerical analysis is conducted for the optimal strategy of platform-mediated reverse factoring financing, as shown in Example 2. For simplicity and accuracy, based on Proposition 3 and the conclusions from Example 1, the following analysis mainly compares the optimal decisions and profits under the



a *b*

Fig. 3. Retailer's order-profits dynamics under credit reputation risks with unsecured third-party guaranteed financing: *a* – order quantity (q_1, q_2); *b* – profit (Π_1^R, Π_2^R)

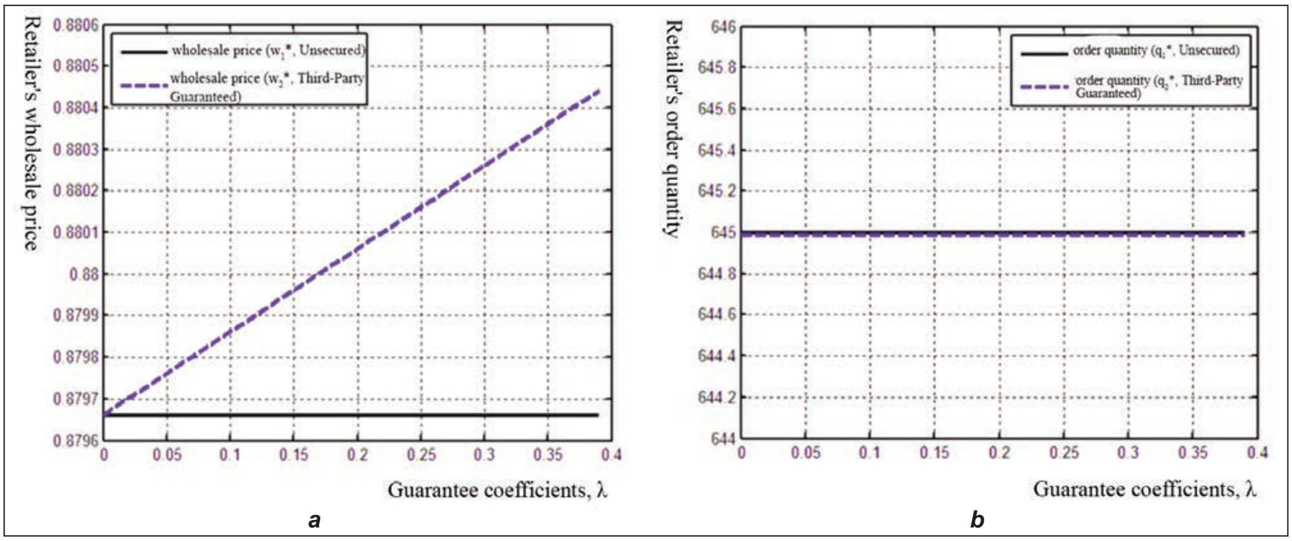


Fig. 4. Optimal supplier-retailer decisions under unsecured and third-party guarantees across guarantee coefficients: *a* – wholesale price (w_1, w_2); *b* – order quantity (q_1, q_2)

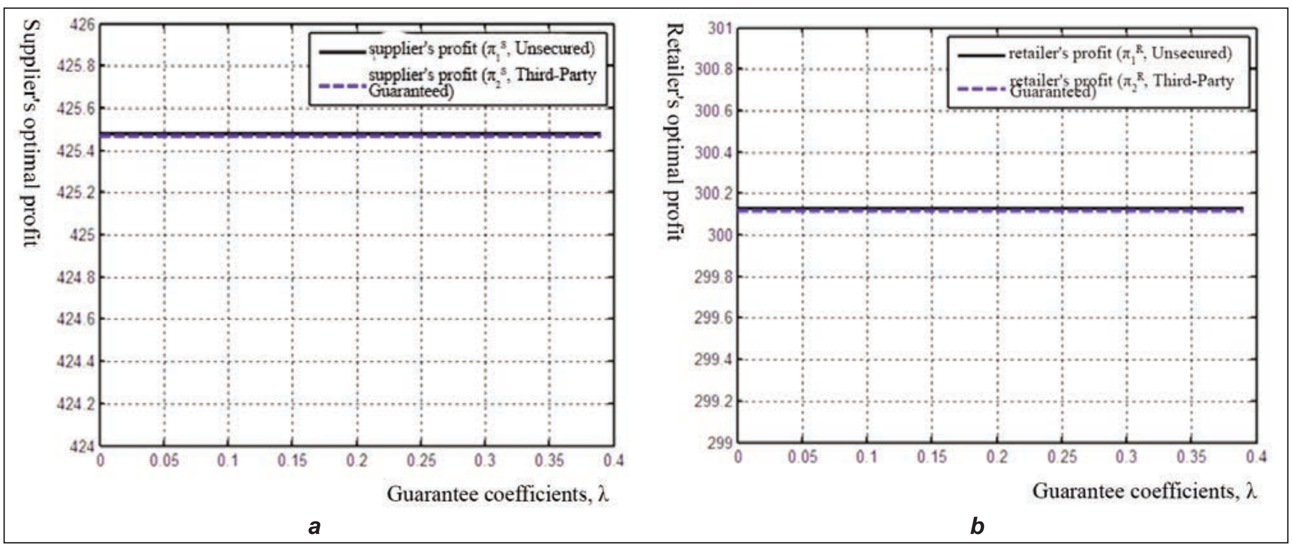


Fig. 5. Optimal supplier-retailer profits under unsecured and third-party guarantees across guarantee coefficients: *a* – supplier's profit (Π_1^S, Π_2^S); *b* – retailer's profit (Π_1^R, Π_2^R)

no-guarantee and platform-mediated financing scenarios.

Example 2: Assume that the retailer's market demand for the product follows a normal distribution with a mean of 300 and a variance of 120. The unit price of the product is p = 1. The capital-constrained supplier has an internal capital level of 0, and the unit production cost of the product is c = 0.2. The factoring company's credit interest rate is r = 0.1. The retailer's optimal decisions and profits as a function of the platform's service fee rate are shown in figure 6.

From figure 6, it can be observed that, consistent with Propositions 4 and 5, in the case of platform-mediated reverse factoring, the retailer's order quantity and optimal profit decrease as the service fee rate increases. Additionally, when the platform's service fee rate is low ($\xi < \hat{\xi} = \frac{l}{A}$), the retailer's order quantity and profit are higher under platform-mediated financing, and the service fee threshold increases with the credit loss risk (or decreases with the credit line).

CONCLUSION

This study investigates a two-tier supply chain comprising a core textile retailer and a capital-constrained textile supplier, analysing how reverse factoring based on accounts receivable can address upstream financing constraints. The paper specifically analyses the impact of the reputation loss risk faced by retailers when engaging in reverse factoring financing and explores the optimal strategies for textile retailers under random market demand conditions.

The paper first clarifies the negative impact of reputation loss risk on financing efficiency. It highlights that external guarantees do not effectively mitigate the reputational risk in reverse factoring financing. Additionally, the study demonstrates that platform-matching reverse factoring financing can reduce the adverse effects of reputation loss risk. The advantage of using platforms increases as the credit limit declines, suggesting that when the platform's service

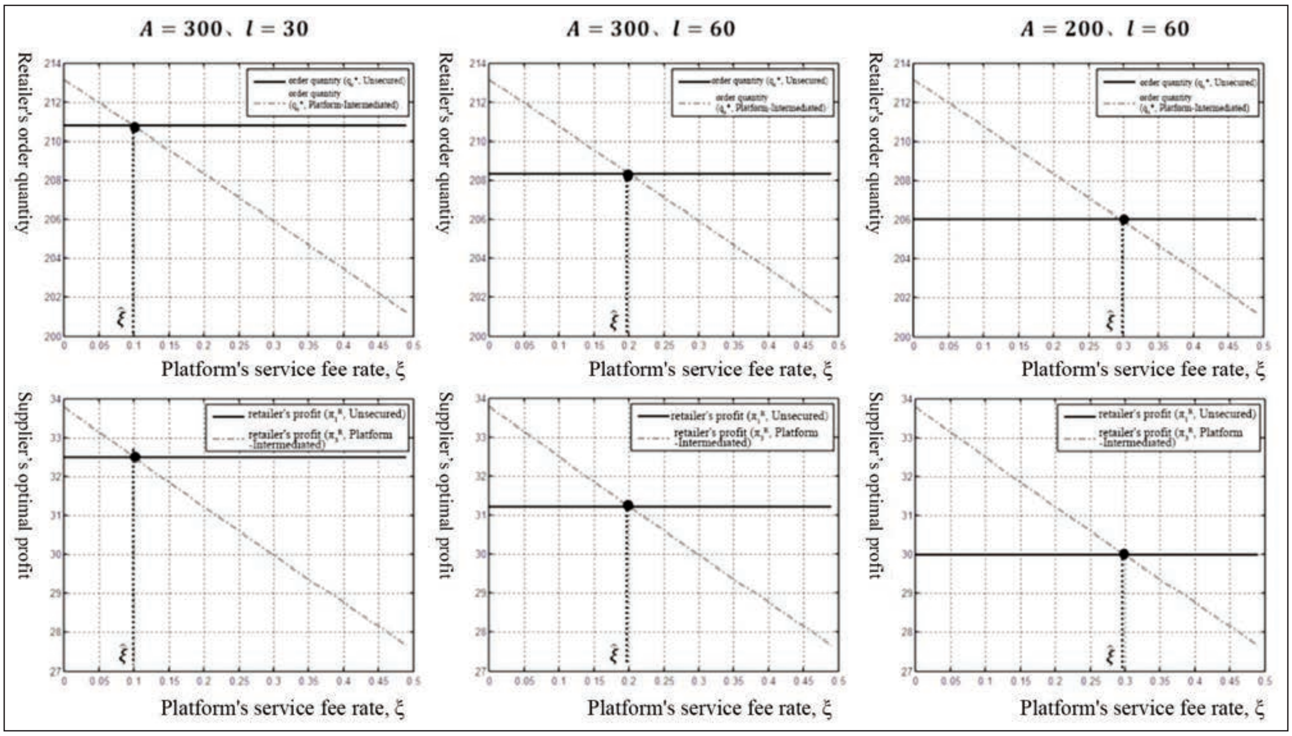


Fig. 6. Retailer's optimal decisions and profitability under unsecured platform-intermediated financing

rate is low, textile retailers should opt for reverse factoring financing through the platform.

The findings provide insights into the optimal approach for core textile enterprises to implement reverse factoring while accounting for reputational risk. The paper also explains why collaborations between core textile enterprises and guarantee companies are rarely seen in reverse factoring financing practices. Moreover, it advises guarantee institutions to refrain from focusing on partnering with core textile enterprises for reverse factoring and suggests that for reverse factoring platforms, reducing service rates when the core enterprise has a high credit limit or a low reputation loss risk can help expand the financing business more effectively.

From a policy standpoint, subsidising platforms with the goal of supporting textile suppliers' development. For suppliers, actively participating in platform financing under low fee rates not only reduces their financing costs but also stabilises their relationships with core textile retailers by avoiding wholesale price hikes.

Despite the contributions of this study, it does have some limitations. For instance, it assumes that financing participants, such as guarantee companies, are risk-neutral and does not take into account the residual value of unsold products at the end of the marketing period. These aspects represent potential directions for future research.

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Economic growth, industrial concentration, and carbon emissions in the textile industry

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FENG LIU FEI ZOU

ABSTRACT – REZUMAT

Economic growth, industrial concentration, and carbon emissions in the textile industry

Against the backdrop of global "dual-carbon" goals and China's economic transformation, the textile industry, as a key high-emission sector, has attracted much attention regarding the dynamic correlations between its carbon emissions, economic growth, and industrial concentration. Based on China's textile industry data from 2001 to 2020, this paper constructs a Vector Autoregression (VAR) model and systematically explores the interactive relationships among the three through methods such as the Granger causality test, the cointegration test, impulse response, and variance decomposition. The findings are as follows: the Granger causality test shows that only the growth rate of carbon emissions in the textile industry (D_CO_2) is a significant Granger cause of changes in industrial concentration (D_IC), while there is no significant causal relationship between other variables, indicating that changes in carbon emissions have a one-way driving effect on the adjustment of industrial concentration; the unrestricted cointegration test indicates that there is one long-term cointegration relationship among the three; in the long-term equilibrium, D_IC has a significant impact on D_CO_2, reflecting that the improvement of industrial concentration can effectively curb carbon emissions; impulse response analysis shows that the response of D_CO_2 to its own shock is significant in the short term, and the impact of D_IC shock on it is transient; D_IC shows a positive response to D_CO_2 shock, while the impact of its own shock is weak; the response of D_ISV (growth rate of economic growth) to D_CO_2 shock lasts longer, and the dynamic interaction among variables is centered on D_CO_2; the variance decomposition results show that the long-term explanatory power of D_CO_2 to D_IC reaches 48.85%, but the explanatory power of D_IC to D_CO_2 is only 11.75%; the impact of D_IC on D_ISV (11.63%) is stronger than that of D_CO_2 (7.32%); in the long run, the forecast error variances of the three variables are mainly dominated by their own shocks (about 80% for D_CO_2 and D_ISV, and about 50% for D_IC), and the system eventually tends to equilibrium. The study reveals the key role of carbon emissions in the textile industry in adjusting industrial concentration, providing empirical evidence for coordinating industrial concentration and carbon emission governance through policy guidance.

Keywords: *economic growth, industrial concentration, carbon emissions in the textile industry, VAR model*

Creșterea economică, concentrarea industrială și emisiile de carbon în industria textilă

Pe fondul obiectivelor globale privind „dubla reducere a emisiilor de carbon" și al transformării economice a Chinei, industria textilă, ca sector-cheie cu emisii ridicate, a atras o atenție sporită asupra corelațiilor dinamice dintre emisiile sale de carbon, creșterea economică și concentrarea industrială. Pe baza datelor privind industria textilă din China din perioada 2001–2020, acest articol construiește un model de autoregresie vectorială (VAR) și explorează sistematic relațiile interactive dintre cele trei elemente prin metode precum testul de cauzalitate Granger, testul de cointegrare, răspunsul la impuls și descompunerea varianței. Concluziile sunt următoarele: testul de cauzalitate Granger arată că doar rata de creștere a emisiilor de carbon din industria textilă (D_CO_2) este o cauză Granger semnificativă a schimbărilor în concentrarea industrială (D_IC), în timp ce nu există o relație cauzală semnificativă între alte variabile, indicând faptul că schimbările legate de emisiile de carbon au un efect de impuls unidirecțional asupra ajustării concentrării industriale; testul de cointegrare fără restricții indică faptul că există o singură relație de cointegrare pe termen lung între cele trei variabile; în echilibrul pe termen lung, D_IC are un impact semnificativ asupra D_CO_2, reflectând faptul că îmbunătățirea concentrării industriale poate reduce în mod eficient emisiile de carbon; analiza răspunsului la impuls arată că răspunsul D_CO_2 la propriul șoc este semnificativ pe termen scurt, iar impactul șocului D_IC asupra acestuia este tranzitoriu; D_IC arată un răspuns pozitiv la șocul D_CO_2; D_IC prezintă un răspuns pozitiv la șocul D_CO_2, în timp ce impactul propriului său șoc este slab; reacția D_ISV (rata de creștere economică) la șocul D_CO_2 durează mai mult, iar interacțiunea dinamică dintre variabile se concentrează asupra D_CO_2; rezultatele descompunerii varianței arată că puterea explicativă pe termen lung a D_CO_2 asupra D_IC ajunge la 48,85%, dar puterea explicativă a D_IC asupra D_CO_2 este de doar 11,75%; impactul D_IC asupra D_ISV (11,63%) este mai puternic decât cel al D_CO_2 (7,32%); pe termen lung, variațiile erorilor de prognoză ale celor trei variabile sunt dominate în principal de propriile șocuri (aproximativ 80% pentru D_CO_2 și D_ISV și aproximativ 50% pentru D_IC), iar sistemul tinde în cele din urmă spre echilibru. Studiul relevă rolul cheie al emisiilor de carbon din industria textilă în ajustarea concentrării industriale, oferind dovezi empirice pentru coordonarea concentrării industriale și a guvernanței emisiilor de carbon prin orientări de politică.

Cuvinte-cheie: *creștere economică, concentrare industrială, emisii de carbon în industria textilă, model VAR*

INTRODUCTION

Against the backdrop of an escalating global climate crisis and China's deepening commitment to its "dual carbon" strategy, the green transformation of traditional manufacturing industries has emerged as a critical breakthrough point for achieving high-quality development [1–3]. As the world's largest producer, consumer, and exporter of textiles, China's textile industry served not only as a vital pillar of the national economy (according to data from the Ministry of Industry and Information Technology, the industrial added value of textile enterprises above designated size increased by 4.4% year-on-year in 2024, with operating revenue reaching 4,953.21 billion yuan, representing a 4.0% year-on-year increase), but also constituted a significant contributor to energy consumption and carbon emissions. It was estimated that the textile and apparel industry accounted for 6% to 8% of global carbon emissions, making it the second-largest consumer and polluter, generating approximately 1.7 billion tonnes of carbon dioxide annually [4]. The textile industry demonstrated a high degree of environmental degradation, with adverse environmental impacts increasing accordingly [5]. The textile industry caused both direct and indirect impacts on environmental degradation, as fossil fuel combustion involved in textile manufacturing processes directly produced greenhouse gases in the atmosphere, whilst indirectly, the textile industry increased toxic emissions generated by higher electricity utilisation rates throughout the entire textile supply chain [6]. Concurrently, China's economy had transitioned from a phase of high-speed growth to one of high-quality development. In 2024, the total GDP exceeded 130 trillion yuan, with per capita GDP surpassing 92,000 yuan, marking a profound transformation in the economic growth model from factor-driven to innovation-driven development, and from scale expansion to quality and efficiency enhancement [7–9].

From a global perspective, climate change has become one of the most severe challenges facing human society. The Sixth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC) indicated that if global warming exceeded 1.5°C, the frequency of extreme weather events would increase threefold, with ecosystem collapse risks rising significantly [10, 11]. As a key participant in global climate governance, China had committed to the international community to achieve the "dual carbon" goals of "carbon peaking before 2030 and carbon neutrality before 2060", which represented not merely environmental constraints but strategic guidance for economic transformation [12, 13]. Within this context, the industrial sector, as a primary source of carbon emissions, had its low-carbon transformation listed as a core task in the "14th Five-Year Plan". The textile industry, as an important component of the industrial system, exhibited typical carbon emission characteristics: on one hand, according to the "Feasibility Study Report on Renewable Energy Investment for Decarbonisation in China's Textile Industry" released by institutions including the China National Textile Information Centre, China's textile fibre processing volume accounted for more than 50% of the global total, with annual carbon emissions from the textile industry comprising approximately 2% of the national total carbon emissions, with industry carbon emissions primarily originating from energy use. The textile industry's energy consumption was dominated by coal and natural gas, and the coal-biased energy structure resulted in carbon emission intensity per unit output being higher than the national industrial average; on the other hand, the textile industry possessed long industrial chains with multiple links (encompassing spinning, weaving, dyeing, and garment production), leading to high end-of-pipe treatment costs and significant technical difficulties [14–16]. Therefore, resolving the textile industry's "high emissions, difficult treatment" dilemma constituted a critical component in implementing the "dual carbon" goals.

Existing research had established a relatively systematic analytical framework for the relationship between economic growth and carbon emissions, with the most representative being the Environmental Kuznets Curve (EKC) hypothesis proposed by Grossman and Krueger (1995), which suggested an "inverted U-shaped" relationship between economic growth and environmental pollution, during the early stages of economic development, accelerated industrialisation processes led to increased pollution emissions; when economic development reached a certain stage, technological progress, industrial structure upgrading, and enhanced environmental awareness would drive emission reductions [17].

Subsequent research further expanded this theory, finding that factors such as energy structure (such as the proportion of fossil energy), technological innovation (such as clean technology research and development), and institutional arrangements (such as environmental regulation) would influence the shape and inflexion point position of the EKC [18]. Research on industrial concentration and carbon emissions primarily focused on two aspects: first, from a market structure perspective, exploring the impact of monopoly or competition levels on corporate environmental behaviour [19]; second, from an industrial organisation perspective, analysing whether increased concentration reduced unit output emissions through economies of scale, scope economies, or technological innovation [20]. For example, some studies argued that leading enterprises in highly concentrated industries possessed greater capacity to undertake environmental protection equipment investments, thereby reducing unit emissions [21]; however, other research indicated that excessive concentration might lead to monopolistic enterprises lacking emission reduction incentives, even evading environmental responsibilities through "pollution transfer". Nevertheless, these studies were predominantly based on general manufacturing or service industry data, with insufficient heterogeneity analysis targeting specific industries (such as the textile industry). As a typical "multi-link, high-energy-consumption, low-value-added" industry, the textile industry's industrial concentration effects on carbon emissions might differ significantly from other industries: for instance, concentration in dyeing processes might reduce marginal costs through shared pollution treatment facilities, whilst concentration in spinning processes might improve energy efficiency through equipment upsizing, but these mechanisms have not yet received systematic verification.

Existing research rarely incorporated economic growth, industrial concentration, and carbon emissions into the same analytical framework to explore the dynamic interactive relationships among the three variables. Economic growth might influence industrial concentration through two pathways: first, the "market expansion effect", economic growth expands market demand, prompting enterprises to scale up and driving concentration increases; second, the "policy guidance effect", governments actively increase concentration through mergers and acquisitions, elimination of backward capacity, and other policies to promote industrial upgrading. Changes in industrial concentration would, in turn, affect carbon emissions through "technological spillover effects" (demonstration effects of leading enterprises), "economies of scale effects" (unit cost reduction), and "regulatory cost effects" (reduced regulatory difficulty). Therefore, economic growth and industrial concentration might not independently influence carbon emissions but rather jointly affect environmental outcomes through complex interactive mechanisms [22–24]. From a theoretical perspective, this paper's exploration contributed to deepening the interdisciplinary research between New Structural Economics and Environmental Economics. By treating industrial concentration as a quantitative indicator of industrial structure and exploring its relationships with economic growth (factor endowment upgrading) and carbon emissions (environmental constraints), this study could provide new theoretical explanations for "how industrial structure upgrading coordinates economic growth with environmental objectives". Additionally, existing research was predominantly based on developed country data, whilst this paper, using China's textile industry as a sample and combining policy practices under the "dual carbon" strategy background, could enrich the theoretical accumulation of green transformation in traditional industries in developing countries. From a practical perspective, the research conclusions of this paper could provide references for policy formulation. On one hand, it could provide empirical evidence for China's textile industry's "clustering and greening" development pathway, for example, how to coordinate industrial concentration enhancement with technological innovation through policy guidance, avoiding "concentration for concentration's sake" that leads to monopolistic lock-in or innovation inertia; on the other hand, it could provide direction for precise environmental regulation design, for example, formulating differentiated technical standards and incentive policies for textile enterprises with different concentration levels (such as providing common pollution treatment technology support for small and medium enterprises in low-concentration industries, and strengthening carbon emission information disclosure for leading enterprises in high-concentration industries) [25, 26].

Based on the aforementioned background and issues, this paper proposes to employ a VAR model to systematically investigate the interactive relationships among economic growth, industrial concentration, and textile industry carbon emissions through Granger causality tests, cointegration tests, impulse response, and variance decomposition methods. Under the dual context of "dual carbon" goals and economic transformation, the green and low-carbon development of the textile industry has become a "mandatory question" for China's industrial transformation and upgrading. This paper focused on the relationships among economic growth, industrial concentration, and textile industry carbon emissions, attempting to answer the core question of "how to achieve carbon emission reduction whilst promoting industrial concentration". Through theoretical analysis and empirical testing, this paper aimed to provide new perspectives for the green transformation of traditional industries and contribute Chinese experience to global climate governance. The subsequent chapters would systematically verify research hypotheses and propose policy recommendations through theoretical frameworks, data descriptions, model specifications, and results analysis.

LITERATURE REVIEW

The relationship between economic growth and carbon emissions

Carbon dioxide emissions could be categorised into natural emissions and anthropogenic emissions. Natural emissions refer to carbon dioxide released into the atmosphere from ecosystems such as soil, oceans, and forests; anthropogenic emissions refer to carbon dioxide emissions caused by human activities, primarily originating from fossil energy consumption and biomass fuel combustion [27]. The relationship between economic growth and carbon emissions constituted one of the core issues in environmental economics, with its theoretical origins traceable to the Environmental Kuznets Curve (EKC) hypothesis. Grossman and Krueger (1995), through their study of the North American Free Trade Area, first proposed that economic growth and environmental pollution exhibited an "inverted U-shaped" relationship, during the early stages of economic development, accelerated industrialisation processes led to surges in energy consumption and pollutant emissions; when economic development reached a certain stage, technological progress, industrial structure upgrading, and enhanced environmental awareness would drive emissions into a declining trajectory [17]. This hypothesis provided a classical analytical framework for understanding the contradiction between “development and pollution”, with subsequent research conducting multidimensional expansions around its mechanisms and applicability. Scholars revealed the formation logic of the EKC from perspectives including energy structure [18], technological innovation [28], and institutional arrangements [29]. The high proportion of fossil energy (particularly coal) was considered a key constraining factor for the “inverted U-shaped” inflection point; technological innovation influenced emissions through two pathways: first, the “substitution effect” (clean energy substituting fossil energy), and second, the “efficiency effect” (declining energy consumption per unit output); environmental regulation (such as carbon taxes and emissions trading) promoted corporate innovation through the “Porter hypothesis”, thereby reducing pollution emissions.

Narayan, Saboori, and Soleymani (2016) argued that if current income levels exhibited positive cross-correlation with past CO_2 emission levels, whilst current income levels demonstrated negative cross-correlation with future CO_2 emissions [30], then over time, CO_2 emissions would decline with increasing income, which aligned with the Environmental Kuznets Curve (EKC) hypothesis. Gbadeyan et al. (2024) contended that economic growth was the primary driving factor for global carbon emission increases, and achieving a carbon-balanced environment required the decoupling of these two variables [31]. Hu et al. (2021) investigated the impact of categorised energy consumption, technological innovation, and economic output on carbon dioxide emissions in India. Their empirical analysis results demonstrated that categorised energy consumption and technological innovation had positive effects on economic growth, whilst the utilisation of renewable energy and technological innovation (namely carbon capture and storage technologies) could significantly reduce carbon dioxide emissions [32].

Zhang (2021) selected panel data from the BRICS countries (Brazil, Russia, India, China, and South Africa) for the period 1990–2019 to empirically study the impact of technological innovation and economic growth on carbon emissions [33]. Granger causality test results indicated that unidirectional causal relationships existed both between technological patents and carbon emissions, and between economic growth and carbon emissions (with the former pointing to the latter). Zhang et al. (2024) employed the entropy method and the coupling coordination model to explore the coordination level between economic growth and carbon emissions. Their research results demonstrated that most Chinese cities had room for improvement in the coordination level between carbon emissions and economic growth [34].

Fu et al. (2024) adopted the Thiel index, Tapio decoupling model, and Logarithmic Mean Divisia Index (LMDI) decomposition method to explore the decoupling between economic growth and carbon emissions. Results indicated that carbon intensity differences primarily originated from disparities between central provinces and underdeveloped western provinces [35]. Hong et al. (2025) analysed the decoupling relationship between carbon emissions and economic growth in China’s textile industry across 30 provinces. Their research results demonstrated that both carbon emissions and GDP growth in China’s textile industry exhibited a “rise-then-decline” pattern, with carbon emissions primarily originating from coal consumption, followed by petrol and natural gas. China’s textile industry achieved strong decoupling between carbon emissions and economic growth, with per capita output value serving as the primary driving factor for carbon emission growth, whilst the energy consumption intensity factor demonstrated the most significant inhibitory effect on carbon emissions [36].

Additionally, some scholars explored the relationship between per capita gross domestic product (GDP) and per capita carbon dioxide emissions, discovering an inverted U-shaped relationship between the two variables. Carbon emissions increased with rising income but at a declining rate, attributed to structural effects and technological effects. When development reached a certain level, namely when structural effects and technological effects offset scale effects, emissions would decrease with increasing income [37].

The relationship between industrial concentration and carbon emissions

Industrial concentration (namely, the market share proportion of leading enterprises within an industry), as a core indicator for measuring market structure, has gradually become a research focus regarding its relationship with carbon emissions in recent years.

Industrial concentration influenced carbon emissions through scale effects and market power. In terms of scale effects, large enterprises in highly concentrated industries might achieve improved energy efficiency through expanded production scales (such as sharing emission reduction technologies and optimising resource allocation), thereby reducing carbon emissions per unit output. For instance, the steel industry could reduce energy waste from redundant construction through capacity integration. However, monopolistic enterprises might delay technological upgrading due to a lack of competitive pressure, leading to increased carbon emissions. Regarding market structure, the concentration measured by the Herfindahl-Hirschman Index (HHI) exhibited a nonlinear relationship with environmental efficiency: initial improvements in concentration might reduce emissions through technological diffusion, but exceeding a threshold might suppress innovation due to market monopolisation, forming a “U-shaped” curve. Additionally, spatial agglomeration in highly concentrated industries might generate synergistic emission reduction effects through infrastructure sharing and technological spillovers, but might also intensify regional environmental pressure due to concentrated pollutant emissions.

Aghion et al. (2005), drawing from Schumpeterian innovation theory, proposed that moderately concentrated market structures (monopolistic competition) were more conducive to enterprise innovation, leading enterprises possessed stronger financial and technological capabilities to undertake environmental research and development costs, thereby reducing emissions per unit output [20]; whilst excessively dispersed market structures (perfect competition) resulted in enterprises struggling to invest in environmental technologies due to minimal profits, leading to a "race to the bottom". Monopolistic enterprises might evade responsibility through "pollution transfer" (such as relocating high-pollution processes to regions with weak regulation), actually exacerbating carbon emissions at the global level.

However, the aforementioned research was predominantly based on general manufacturing industries (such as automotive and chemical), with insufficient specific analysis targeting the textile industry. The textile industry's uniqueness lay in: firstly, its long industrial chains (encompassing spinning, weaving, dyeing, and garment production), where dyeing processes accounted for 40% of the industry's energy consumption and 60% of water consumption, yet dyeing enterprises were typically small-scale and dispersed, resulting in significant industry heterogeneity in concentration; secondly, the textile industry belonged to the "low value-added, high emission" category, where enterprises operated with limited profit margins, and the environmental investment capabilities of leading enterprises differed substantially from small and medium enterprises, potentially altering the traditional direction of industrial concentration's effect on carbon emissions.

The relationship between economic growth, industrial concentration, and carbon emissions

Within existing research, discussions incorporating economic growth, industrial concentration, and carbon emissions into the same framework were relatively limited, with two primary perspectives existing, as detailed below.

The impact of synergistic effects between economic growth and industrial concentration on carbon emissions

The interactive effects of economic growth and industrial concentration on carbon emissions varied according to economic development stages and industry characteristics. Some studies found that during periods of rapid economic growth, increases in industrial concentration might exacerbate carbon emissions, particularly in energy-intensive industries. For example, in regions with rapid economic growth, high industrial concentration often accompanied higher carbon emission intensity, as large enterprises tended to expand capacity rather than adopt clean technologies. Cole and Elliott (2003) indicated that industrial concentration in developing countries might reinforce "scale effects", where enterprises pursued profits through increased output rather than improved energy efficiency [38]. In developed countries, due to stringent environmental regulations and more advanced technology, high industrial concentration might promote green innovation, thereby reducing carbon emissions per unit output [39].

Industrial concentration moderates the carbon intensity effect on economic growth

Industrial concentration might regulate the impact of economic growth on carbon emissions by altering market competition structures. On one hand, large enterprises in highly concentrated industries might possess stronger research and development capabilities, promoting low-carbon technological progress, thereby offsetting carbon emission increases brought by economic growth. Porter and Linde's (1995) "Porter hypothesis" argued that moderate market concentration could incentivise enterprises to invest in environmental technologies, particularly under policy guidance. Carbon intensity in highly concentrated industries might decline more rapidly with economic growth, as these industries more easily form technological alliances and share emission reduction technologies [29]. On the other hand, if industrial concentration led to monopolies or oligopolies, enterprises might lack emission reduction motivation, even hindering policy implementation. Jaffe et al. (2005) indicated that certain highly concentrated industries (such as fossil energy) might lobby governments to relax environmental regulation, thereby exacerbating the carbon footprint of economic growth [28]. Therefore, the moderating effect of industrial concentration on the relationship between economic growth and carbon emissions depended on whether market structures promoted or suppressed green innovation [40, 41].

Research review

Research on carbon emissions in the textile industry primarily focused on the following three aspects within existing literature: emission characteristic identification, driving factor analysis, and emission reduction pathway exploration. Economic growth and industrial concentration jointly influenced carbon emissions through scale, structural, and technological effects. Although the Environmental Kuznets Curve provided a basic framework, the role of industrial concentration highlighted the necessity for targeted policies to mitigate pollution in concentrated industries.

Existing research still exhibited the following limitations: the role of industrial concentration had not been adequately emphasised, most studies treated industrial concentration as an exogenous variable, failing to thoroughly explore how it influenced carbon emissions through mechanisms such as scale effects and technological diffusion; the interactive mechanisms between economic growth and industrial concentration remained unclear, systematic analysis was lacking regarding "how economic growth promoted industrial concentration increases" and "how concentration increases reacted upon carbon emissions";

industry-specific analysis was insufficient, the textile industry possessed long industrial chains with strong link heterogeneity (such as significant differences in emission characteristics between dyeing and spinning), yet existing research predominantly treated it as a homogeneous industry, failing to discuss link differences.

Based on the aforementioned academic trajectory and practical demands, this paper's contributions were reflected in the following aspects: expansion of theoretical frameworks, for the first time incorporating economic growth, industrial concentration, and textile industry carbon emissions into a unified analytical framework, systematically revealing the dynamic interactive mechanisms among the three variables.

RESEARCH DESIGN

Variable selection

This study primarily analysed the relationships between economic growth, industrial concentration, and carbon emissions in China's textile industry from 2001 to 2020. The data for economic growth and industrial concentration employed in this study were primarily sourced from successive editions of the China Statistical Yearbook and China Industrial Statistical Yearbook, with missing data supplemented using interpolation methods. Carbon dioxide emission data were obtained from the China Emission Accounts and Datasets (CEADs), utilising textile industry emission data for the period 2001–2020. This database (https:// derived carbon dioxide emissions from sources including coking products, crude oil, petrol, kerosene, diesel, fuel oil, liquefied petroleum gas, refinery gas, other petroleum products, natural gas, heating, electricity, and other energy sources [42, 43].

Economic growth

This study employed Industrial Sales Value (ISV) to represent economic growth. The core meaning of ISV referred to the monetary representation of the total volume of industrial products sold by industrial enterprises within a specific period, encompassing both the value of products sold from current production and the value of products sold from previous inventory [44, 45].

Industrial concentration

Industrial concentration referred to the degree of dominance that a few enterprises within a particular industry exercised over aspects such as production volume, sales volume, and total assets within that market [46]. It was generally expressed as the percentage that a specific indicator (most commonly the sales revenue indicator) of the several largest enterprises in a market represented of the industry total [47]. Moderately high industrial concentration could improve efficiency, thereby reducing carbon emissions. This study, referencing the aforementioned definition and combining it with the actual circumstances of the textile industry, employed the proportion of large and medium textile enterprises' annual output value to the total annual sales value of textile enterprises. Textile industry concentration was calculated according to the following formula:

$$IC = LMG_{GDP} / ISV \tag{1}$$

where *IC* represented textile industry concentration, *LMG* denoted the annual output value of large and medium enterprises, and *ISV* represented the annual sales value of the textile industry.

Textile industry carbon emissions.

This study employed a mass balance approach to calculate carbon emissions based on IPCC guidelines (IPCC, 2006), with the formula as follows:

$$CE_i = AD_i \times NCV_i \times CC_i \times O \tag{2}$$

where CE_i denoted CO_2 emissions from *i*-type fossil fuels, including coal, gas, fuel oil, coke, and others; AD_i represented the combustion amount of *i* fossil fuel; NCV_i referred to the "net calorific value", namely the heat value per physical unit after combustion of *i* fossil fuel; CC_i was the "carbon content" of *i* fossil fuel, which quantified the carbon emissions per unit of net calorific value generated; and referred to "oxidation efficiency", *O* representing the oxidation ratio during the fossil fuel combustion process.

Process-related emissions referred to CO_2 emissions in industrial production that originated from industrial raw materials rather than fossil fuels [48]. According to IPCC guidelines (IPCC, 2006), process-related emissions could be calculated as follows:

$$CE_t = AD_t \times EF_t \tag{3}$$

where CE_t represented process-related emissions in production; AD_t denoted activity data related to process-related emissions; and EF_t referred to emission factors.

Figure 1 illustrated the temporal trends of three indicators from 2001 to 2020, as follows: Industrial sales value (logarithmic) exhibited an overall pattern of

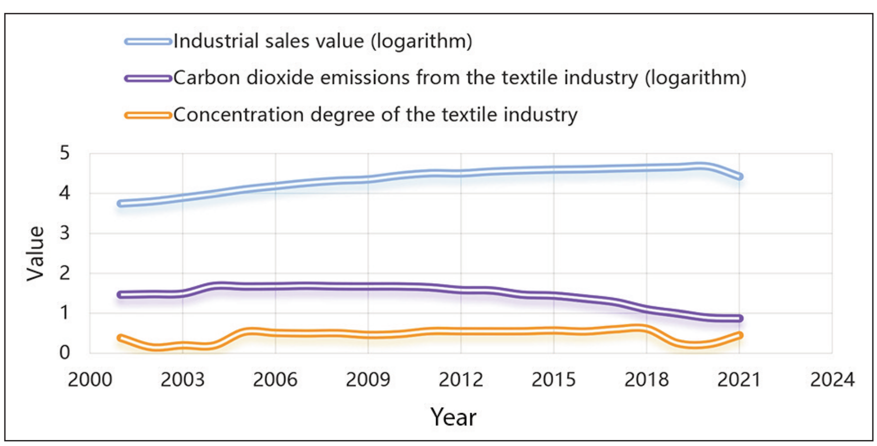

Fig. 1. Trends in economic growth, concentration, and carbon emissions in the textile industry

Table 1

ADF UNIT ROOT TEST					
Variables	Test form	ADF unit root test	ADF unit root test	Test critical value	Conclusion
	(c, t, k)	P value	T statistics	1% level	
CO_2	(c, t, 0)	0.685	–1.756	–4.532	Non-stationary
IC	(c, t, 0)	0.825	–1.406	–4.533	Non-stationary
ISV	(c, t, 0)	0.841	–1.354	–4.533	Non-stationary
D(CO_2)	(c, t, 0)	0.004	–5.097	–4.571	Stationary
D(IC)	(c, t, 0)	0.002	–5.425	–4.572	Stationary
D(ISV)	(c, 0, 0)	0.005	–4.249	–3.857	Stationary

Note: c includes the intercept term; t includes the trend term; k is the automatically selected lag order of the difference term. All numbers are rounded to three decimal places.

gradual increase followed by slight stabilisation, indicating that industrial sales scale experienced moderate growth over time. Textile industry concentration demonstrated relatively low values with minimal overall fluctuations, reflecting changes in the degree of market concentration within the textile industry. The small fluctuations indicated that the level of industry concentration remained relatively stable throughout the study period. Textile industry carbon dioxide emissions (logarithmic) displayed minor fluctuations in the early period, followed by a declining trend in the latter period. The later decline reflected the industry's achievements in emission reduction and related initiatives.

Model specification

The VAR model constructed each endogenous variable in the system as a function of lagged values of all endogenous variables in the system, thereby extending the univariate autoregressive model to a "vector" autoregressive model composed of multivariate time series variables [49]. For a k-dimensional time series $Y_t = (y_{1t}, y_{2t}, \ldots, y_{kt})'$, the mathematical expression for a p-order VAR model denoted as $VAR(p)$ was:

$$Y_t = \Phi_1 Y_{t-1} + \Phi_2 Y_{t-2} + \cdots + \Phi_p Y_{t-p} + \epsilon_t \qquad (4)$$

where Y_t represented a $k{\times}1$ dimensional endogenous variable vector, Φ_i $(i = 1, 2, \ldots, p)$ represented $k{\times}k$ dimensional coefficient matrices, ϵ_t represented a $k{\times}1$ dimensional random error vector, also referred to as innovation, with ϵ_t typically assumed to follow a multivariate normal distribution with zero mean and covariance matrix Σ, namely $\epsilon_t \sim N(0,\Sigma)$.

EMPIRICAL TESTING

Unit root testing

During the modelling process of Vector Autoregression (VAR) models, unit root testing constituted a crucial step, with its core purpose being to determine the stationarity of variables, thereby avoiding issues such as "spurious regression" in the model. Following the Augmented Dickey-Fuller (ADF) unit root tests conducted on textile industry economic growth, industrial concentration, and carbon emissions, the results were presented in table 1. All series achieved stationarity at the first difference, namely I(1).

Stationarity test

The impulse response and variance decomposition require the VAR system to be stable. According to table 2 and figure 2, the reciprocals of the magnitudes of all AR roots are located within the unit circle, so the VAR system can be judged to be stable.
No root lies outside the unit circle. VAR satisfies the stability condition.

Table 2

VAR SYSTEM STABILITY CONDITION TEST	
Root	Modulus
–0.750272	0.750272
0.442100 – 0.507967i	0.673411
0.442100 + 0.507967i	0.673411
0.036861 – 0.598203i	0.599338
0.036861 + 0.598203i	0.599338
–0.264461	0.264461

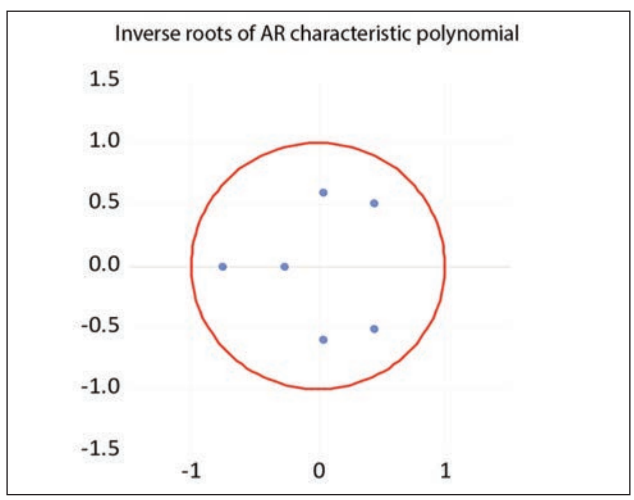

Fig. 2. AR root plot

Granger causality testing

Granger causality testing was employed to determine whether lagged terms of one variable contributed to

Table 3

VAR GRANGER CAUSALITY/BLOCK EXOGENEITY WALD TESTS			
Dependent variable: D_CO_2			
Excluded	Chi-sq	df	Prob.
D_IC	1.946045	2	0.3779
D_ISV	1.450972	2	0.4841
All	3.866399	4	0.4244
Dependent variable: D_IC			
Excluded	Chi-sq	df	Prob.
D_CO_2	11.42633	2	0.0033
D_ISV	0.391444	2	0.8222
All	11.73549	4	0.0194
Dependent variable: D_ISV			
Excluded	Chi-sq	df	Prob.
D_CO_2	1.127565	2	0.5691
D_IC	0.900819	2	0.6374
All	1.638014	4	0.8019

predicting another variable. If lagged terms of variable *X* could significantly improve the prediction accuracy of variable *Y*, this was termed "X Granger-causes Y". The results presented in table 3 revealed the following findings:

(1) The lagged terms of both textile industry concentration (D_IC) and industrial sales value (D_ISV) failed to significantly explain variations in CO_2 emissions, indicating that the influence of economic activities (IC and ISV) on carbon emissions was not statistically significant.

(2) The lagged terms of textile industry CO_2 emissions could significantly explain variations in industrial concentration, potentially reflecting the constraining effects of environmental policies (such as carbon reduction initiatives) on industrial production agglomeration. Industrial sales value (D_ISV) demonstrated no significant impact on industrial concentration (D_IC), possibly suggesting a disconnection between industrial production and sales processes (such as inventory accumulation).

(3) Both textile industry carbon emissions (D_CO_2) and industrial concentration (D_IC) failed to significantly explain variations in industrial sales value, potentially indicating that the sales segment was more influenced by external market demand (such as exports and consumption) rather than internal production factors.

Determination of the VAR model lag length

The selection of an optimal lag length ensured that the stochastic disturbance terms of the VAR model followed vector white noise properties. The calculation results were presented in table 4. All five criteria employed in this study indicated a first-order lag length; therefore, VAR(1) was selected for subsequent analysis.

Cointegration testing

Many economic variables exhibited persistent upward or downward movements, a characteristic that could be generated by stochastic trends in integrated variables. When the same stochastic trends jointly drove a group of integrated variables, this was termed cointegration [50, 51]. Under such circumstances, certain linear combinations of integrated variables remained stationary, and these linear combinations that linked variables with common trend paths were referred to as cointegrating relationships. Cointegrating relationships could be realised through reparameterising VAR models into Vector Error Correction Models (VECM). Cointegration analysis was primarily applied to economic systems where short-term dynamic relationships were easily subject to significant influence from stochastic disturbances, whilst long-term relationships were constrained by equilibrium relationships.

Establishment of the VAR system

Initially, a VAR system was established, with results presented in table 5.

Model validity testing

Firstly, residual autocorrelation was examined. Autocorrelation plots were employed for this examination, which were utilised to demonstrate autocorrelation relationships between different time series data. If the results did not exceed twice the asymptotic standard error of lags, this indicated that the residuals estimated by the VAR model exhibited no cross-correlation. The results reported in figure 3 demonstrated that no cross-correlation existed among the residuals of the variables. The residual series exhibited no significant autocorrelation at various lag orders, satisfying the white noise requirements for VAR model residuals, indicating that the model possessed satisfactory residual characteristics.

Secondly, normality testing was conducted. The residuals were tested to determine whether they followed a normal distribution. As demonstrated in table 6, all test p-values were substantially greater than 0.05 (significance level), failing to reject the null hypothesis that "residuals follow a multivariate normal distribution". This indicated that the distributional characteristics of model residuals conformed to the fundamental assumptions of VAR models, ensuring that subsequent residual-based analyses (such as

Table 4

VAR LAG ORDER SELECTION CRITERIA CALCULATION RESULTS						
Lag	**LogL**	**LR**	**FPE**	**AIC**	**SC**	**HQ**
0	–261.4319	NA	2.46e+08	27.83493	27.98406	27.86017
1	–189.6200	113.3871*	337291.7*	21.22316*	21.81965*	21.32411*

Note: *, *, *** denoted significance levels of 10%, 5%, and 1%, respectively.

Table 5

VECTOR AUTOREGRESSION ESTIMATES			
Variable	**D_CO_2**	**D_IC**	**D_ISV**
$D\_CO_2(-1)$	0.222551	0.016860	48.91746
	(0.25211)	(0.00437)	(63.0546)
	[0.88277]	[3.86108]	[0.77580]
D_IC(–1)	5.725383	–0.032026	595.3975
	(10.2250)	(0.17710)	(2557.40)
	[0.55994]	[–0.18083]	[0.23281]
D_ISV(–1)	–0.001323	–2.60E-06	–0.069728
	(0.00107)	(1.9E-05)	(0.26748)
	[–1.23709]	[–0.14017]	[–0.26068]
C	1.978443	0.027990	2494.721
	(2.78291)	(0.04820)	(696.040)
	[0.71093]	[0.58068]	[3.58416]

Table 6

VAR RESIDUAL NORMALITY TESTS				
Component	**Skewness**	**Chi-sq**	**df**	**Prob.***
1	–0.044098	0.005834	1	0.9391
2	–0.213355	0.136561	1	0.7117
3	–0.188277	0.106345	1	0.7443
Joint	-	0.24874	3	0.9694
Component	Kurtosis	Chi-sq	df	Prob.
1	4.009822	0.764806	1	0.3818
2	3.319216	0.076424	1	0.7822
3	3.348225	0.090945	1	0.763
Joint	-	0.932176	3	0.8177
Component	Jarque-Bera	df	Prob.	
1	0.77064	2	0.6802	
2	0.212985	2	0.899	
3	0.197291	2	0.9061	
Joint	1.180916	6	0.9778	

Note: * Approximate p-values do not account for the coefficient.

impulse response and variance decomposition) yielded highly reliable results. From the perspective of residual normality, the current VAR model specification was deemed reasonable.

Therefore, following the aforementioned analysis, there existed sufficient grounds to conclude that the VAR model specification contained no bias and was stable.

Thirdly, the White heteroskedasticity test was conducted. The joint test results, as presented in table 7, demonstrated a p-value of 0.6448 > 0.05 (significance level), failing to reject the null hypothesis. This indicated that from an overall perspective, the VAR model residuals exhibited no significant heteroskedasticity, satisfying the assumption of “constant residual variance”.

Table 7

JOINT TEST		
Chi-sq	**df**	**Prob.**
66.99416	72	0.6448

The individual components results, as presented in table 8, revealed the following findings: The residual squared terms (res1res1, res2res2, res3res3) exhibited Chi-sq(12) corresponding p-values of 0.1560, 0.7317, and 0.8718, respectively, all substantially greater than 0.05, indicating that individual variable residual squared terms demonstrated no significant heteroskedasticity (namely, each variable’s residual variance remained constant). The residual cross-terms (res2res1, res3res1, res3res2) exhibited Chi-sq(12) corresponding p-values of 0.2447, 0.4337, and 0.6797, respectively, all greater than 0.05, indicating that covariances between residuals also demonstrated no significant heteroskedasticity (namely, inter-variable residual correlation fluctuations remained constant). Other auxiliary indicators (R-squared and F-statistics) demonstrated that individual terms’ R-squared values were generally low (except for res1*res1), whilst F-statistic p-values were all greater than 0.05, further supporting the conclusion of “no significant heteroskedasticity”.

The joint test p-value (0.6448) and all individual component test p-values exceeded 0.05, failing to reject the null hypothesis of “no significant heteroskedasticity in residuals”. This indicated that the VAR model residuals exhibited no heteroskedasticity, satisfying the fundamental assumption of “constant variance” for model residuals. From the perspective of heteroskedasticity, the current model’s estimation results were reliable, with subsequent analyses (such

Table 8

INDIVIDUAL COMPONENTS					
Dependent	**R-squared**	**F(12,4)**	**Prob.**	**Chi-sq(12)**	**Prob.**
res1*res1	0.990185	33.62979	0.002	16.83315	0.156
res2*res2	0.509361	0.346052	0.9311	8.659129	0.7317
res3*res3	0.398821	0.221133	0.9815	6.77996	0.8718
res2*res1	0.878855	2.418189	0.2043	14.94053	0.2447
res3*res1	0.714696	0.835012	0.6386	12.14984	0.4337
res3*res2	0.545278	0.399715	0.902	9.269722	0.6797

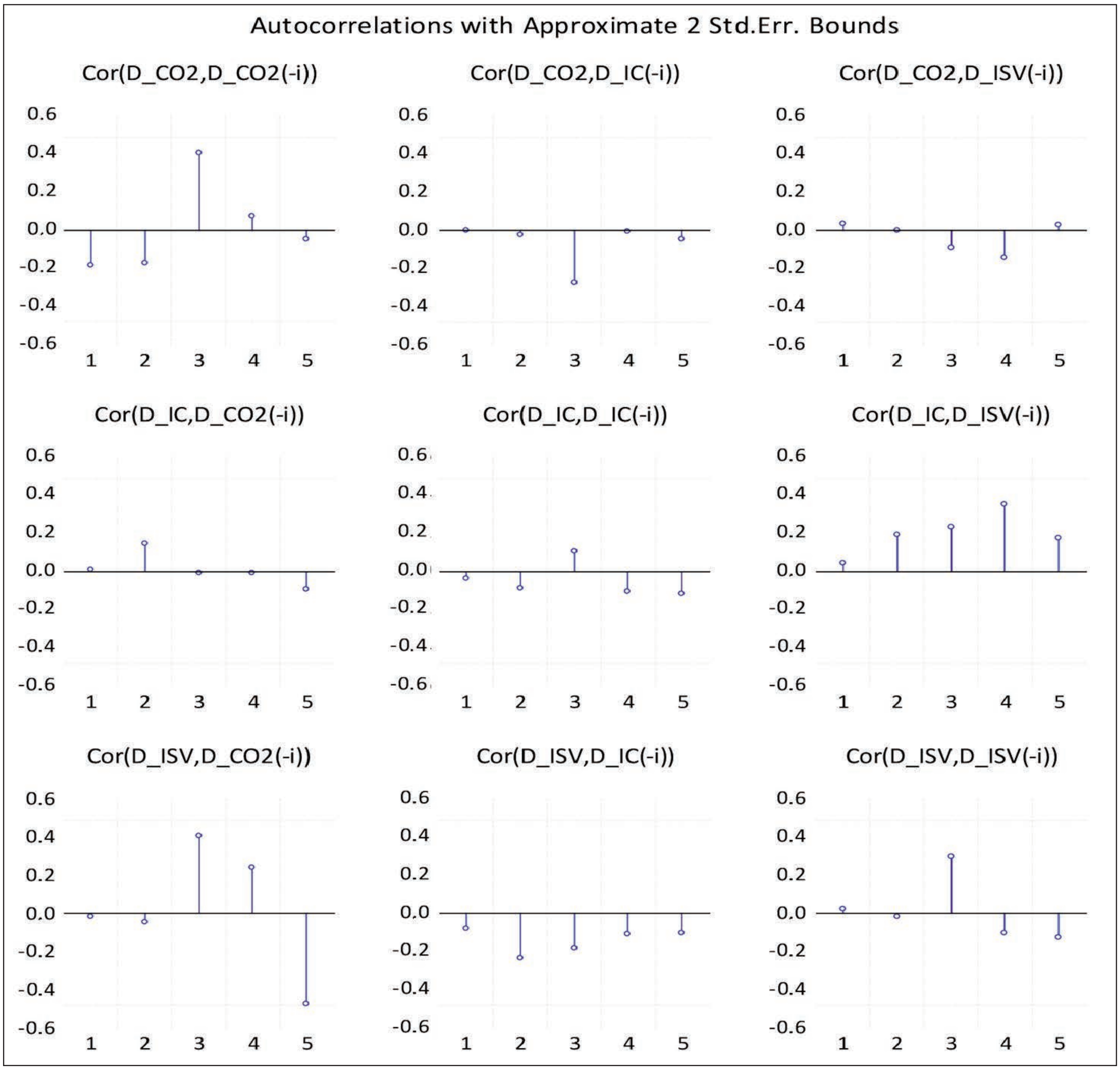

Fig. 3. Autocorrelation plot

as impulse response and variance decomposition) experiencing minimal interference from residual fluctuations [52, 53].

Cointegration analysis

Following the establishment of the VAR system, cointegration testing was subsequently conducted, with test results presented in tables 9 and 10. The results from table 8 demonstrated that at the 0.05 significance level, cointegrating relationships existed between the textile industry carbon emission change rate (D_CO_2), economic growth change rate (D_ISV), and industrial concentration change rate (D_IC), specifically revealing the existence of one cointegrating relationship. Table 9 presents the standardised cointegrating vectors under the existence of cointegrating relationships. The cointegrating vector could be expressed as:

$$D\_CO_2 = -23.61231 D\_IC + 0.001343 D\_ISV \quad (5)$$

Table 9

NON-RESTRICTED COINTEGRATION RANK TEST (TRACE)				
Hypothesised No. of CE(s)	**Eigenvalues**	**Trace statistics**	**0.05 threshold**	**Prob.****
None *	0.757291	32.06473	29.79707	0.027
At most 1	0.291256	9.410421	15.49471	0.3288
At most 2 *	0.216427	3.902249	3.841465	0.0482

Note: Trace test indicates 1 cointegrating equation(s) at the 0.05 level.

Table 10

NORMALIZED COINTEGRATION COEFFICIENT (STANDARD ERROR IN PARENTHESES)		
D_CO_2	D_IC	D_ISV
1	23.61231	–0.001343
-	(20.2206)	(0.00133)

From the cointegrating equation, it could be observed that each unit increase in the economic growth change rate resulted in a 0.001343 unit increase in the carbon emission change rate; conversely, each unit increase in the industrial concentration change rate resulted in a 23.61231 unit decrease in the carbon emission change rate.

VAR IMPULSE RESPONSE AND VARIANCE DECOMPOSITION

Impulse response

The impulse response function, based on the VAR model, characterised time-varying causal associations and shock attenuation characteristics between variables through simulating dynamic transmission of structured shocks (orthogonalised innovations identified through Cholesky decomposition). This study focused on a three-variable system (textile industry carbon emission change rate D_CO_2, industrial concentration change rate D_IC, and economic growth change rate D_ISV), employing first-difference series (implying the premise that original series were non-stationary but became stationary after differencing), to analyse immediate response, persistence, and convergence of shocks, thereby revealing dynamic interactive patterns between variables, as illustrated in figures 4 (1–9).

Figure 4-1 demonstrated that D_CO_2's response to its own shock exhibited strong short-term inertial dependence following the shock (violent fluctuations in periods 1–3), reflecting the series's own dynamic memory characteristics. After period 4, rapid convergence to zero occurred, conforming to the mean-reverting characteristics of a stationary series and validating the stationarity assumption of the differenced series.

Figure 4-2 illustrates D_CO_2's response to D_IC shocks. Structured shocks from D_IC triggered short-term negative deviations in D_CO_2 (significantly negative in periods 1–3), followed by asymptotic convergence, indicating that D_IC exerted short-term inhibitory effects on D_CO_2, but demonstrated no long-term cointegrating relationship (long-term response returned to equilibrium).

Figure 4-3 presents D_CO_2's response to D_ISV shocks. Under D_ISV shocks, D_CO_2 exhibited only weak fluctuations in periods 1–2, rapidly converging to a steady state, indicating that D_ISV's dynamic influence on D_CO_2 was brief and marginal, with low short-term correlation between the two variables.

Figure 4-4 displayed D_IC's response to D_CO_2 shocks. D_CO_2 shocks triggered immediate positive impulses in D_IC (significantly positive in periods 1–2), followed by attenuated oscillations (small fluctuations in periods 3–6), ultimately converging. This

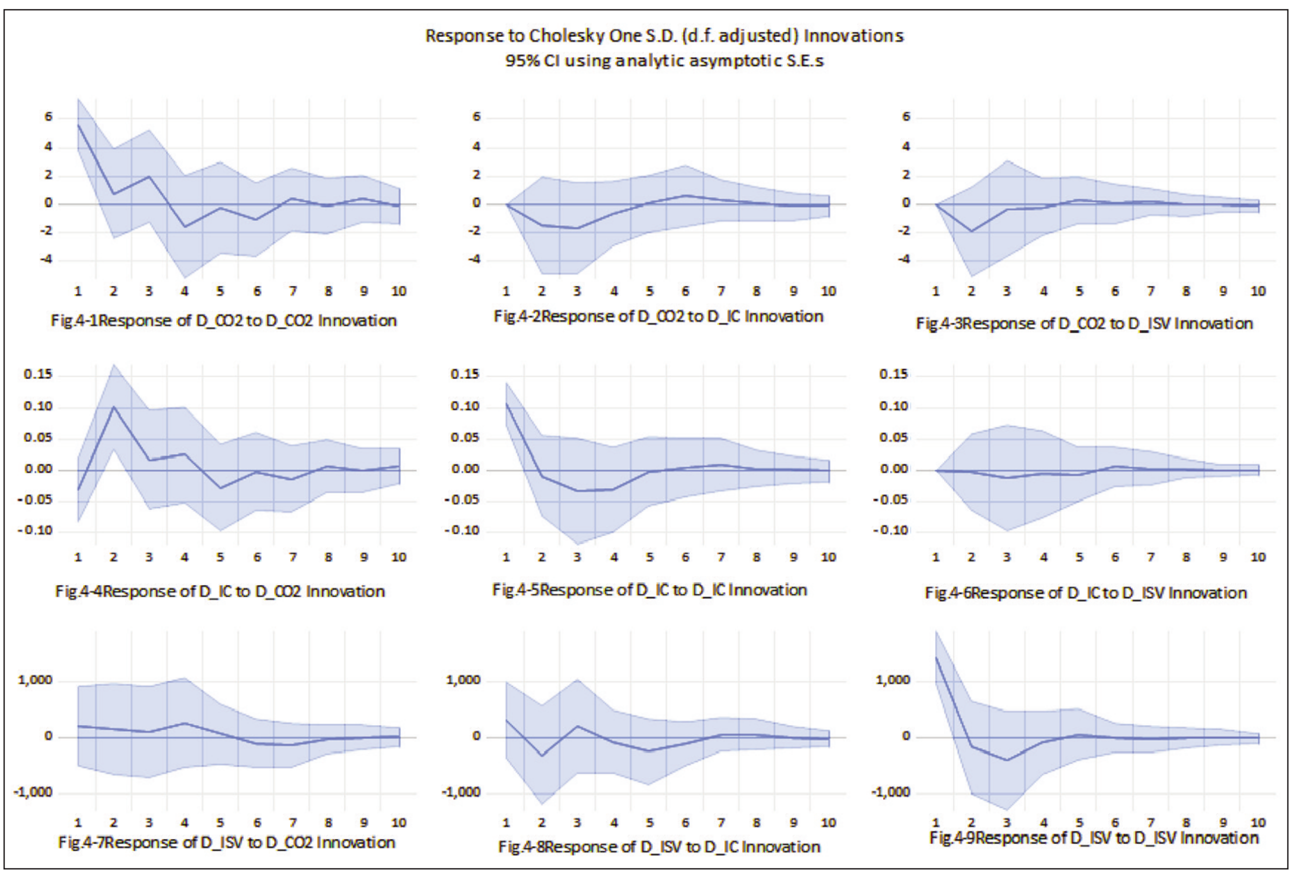

Fig. 4. Impulse response function distribution

reflected that D_CO_2 exerted short-term positive transmission effects on D_IC, but demonstrated no sustained cumulative impact.

Figure 4-5 showed D_IC's response to its own shocks. Under self-shocks, D_IC exhibited weak inertial characteristics (small fluctuations in periods 1–3), rapidly converging to zero, indicating that the D_IC series possessed low dynamic autocorrelation and brief memory effects from self-shocks.

Figure 4-6 represented D_IC's response to D_ISV shocks. The impact of D_ISV shocks on D_IC was completely covered by confidence intervals (fluctuation amplitude approached zero), indicating extremely weak dynamic correlation between the two variables, with D_ISV shocks unable to effectively explain D_IC fluctuations.

Figure 4-7 depicts D_ISV's response to D_CO_2 shocks. D_CO_2 shocks induced sustained medium-term fluctuations in D_ISV (significant deviations from steady state in periods 1–4), with convergence speed slower than other variables' responses to D_CO_2, indicating that D_CO_2 exerted strong intertemporal transmission effects on D_ISV, with more persistent dynamic correlation between the two variables.

Figure 4-8 illustrates D_ISV's response to D_IC shocks. D_IC shocks resulted in short-term negative adjustments in D_ISV (significantly negative in periods 1–2), followed by rapid convergence, reflecting that D_IC exerted instantaneous negative shocks on D_ISV, but demonstrated no long-term effects.

Figure 4-9 presents D_ISV's response to its own shocks. Under self-shocks, D_ISV exhibited high volatility characteristics (large amplitude in periods 1–3), but still satisfied asymptotic convergence (returning to steady state after period 6), validating the stationarity of the differenced series whilst reflecting strong short-term dynamic volatility in D_ISV itself.

Variance decomposition

This study employed the Monte Carlo method to calculate standard errors, with results presented in tables 11, 12 and 13. The "Period" in the tables referred to the number of shock response periods, typically employed to measure the time span of dynamic influences between variables. The specific meaning requires a definition in conjunction with the data frequency employed in the research (such as annual, quarterly, or monthly). If the study utilised annual data, "Period 1" represented the first year following the shock occurrence, "Period 2" represented the second year, and so forth, with "Period 10" indicating the tenth year. If quarterly data were employed, "Period" represented quarters (such as Period 1 for the first quarter, Period 4 for the first year, and Period 10 for the second quarter of the second year).

Table 11 revealed that the variance decomposition of D_CO_2 demonstrated self-shock dominance in long-term explanatory power. The variance decomposition results indicated that the forecast error variance of D_CO_2 across different periods was primarily explained by its own shocks, whilst the influences of other variables (D_IC and D_ISV) remained weak and gradually stabilised.

Short-term (Period 1): The forecast error variance of D_CO_2 was 100% explained by its own shocks, with explanation proportions of D_IC and D_ISV equalling zero. This conformed to the short-term characteristics of variance decomposition–current period shocks originated solely from the variable itself.

Medium-term (Periods 2–5): As periods increased, D_CO_2's own explanation proportion declined slowly from 84.71% in Period 2 to 80.73% in Period 5. D_IC's explanation proportion increased from 5.63% to 11.20%, whilst D_ISV's explanation proportion fluctuated modestly between 9.65% and 8.07%. This indicated that shocks from other variables began influencing D_CO_2, though their impact remained limited.

Long-term (Periods 6–10): The explanation proportions of all variables converged to stability: D_CO_2 itself maintained 80.40% – 80.89%, D_IC stabilised around 11.20%, and D_ISV stabilised between 7.89% – 8.07%. The Monte Carlo simulation standard errors (lower values) demonstrated that the uncertainty of each estimate was relatively small (such as the Period 10 standard error for D_CO_2 being 18.52% and D_IC being 16.44%), indicating robust results.

Overall, the dynamic changes in D_CO_2 were primarily driven by its own shocks, whilst external shocks from D_IC and D_ISV demonstrated weak explanatory power for its forecast error, with long-term influences stabilising.

Table 12 revealed that the variance decomposition of D_IC demonstrated joint dominance by D_CO_2 and its own shocks. The forecast error variance explanation of D_IC exhibited characteristics of "short-term self-dominance with significant medium-term D_CO_2 shock intervention", whilst D_ISV's influence remained consistently weak.

Short-term (Period 1): The forecast error variance of D_IC was 91.70% explained by its own shocks, with D_CO_2 explaining 8.30% and D_ISV's explanation proportion equalling zero, indicating that short-term fluctuations primarily originated from itself.

Medium-term (Periods 2–5): In Period 2, D_CO_2's explanation proportion increased substantially to 49.75%, approaching D_IC's own 50.18%.

Subsequently, D_CO_2's explanation proportion stabilised between 47.06% –48.59%, whilst D_IC's own explanation proportion maintained 50.16% – 52.10%. D_ISV's explanation proportion remained consistently below 1% (with the highest being 0.97% in Period 5). These results indicated that D_CO_2 shocks exerted a significant influence on D_IC's forecast error, with explanatory power comparable to D_IC's own shocks.

Long-term (Periods 6–10): D_CO_2's explanation proportion stabilised between 48.50% – 48.85%, D_IC

Table 11

D_CO_2 VARIANCE DECOMPOSITION RESULTS				
Variance decomposition of D_CO_2	**S.E.**	**Impulse variable**		
Period		**D_CO_2**	**D_IC**	**D_ISV**
1	5.577149	100	0	0
		0	0	0
2	6.116735	84.71435	5.631571	9.654076
		(16.327)	(12.3785)	(12.7677)
3	6.660988	80.70884	10.97088	8.320283
		(18.8439)	(16.2497)	(12.9827)
4	6.866545	80.88623	11.21932	7.894451
		(19.9771)	(16.1148)	(12.5962)
5	6.876662	80.73444	11.1959	8.069658
		(20.3706)	(16.8598)	(12.4715)
6	6.985099	80.53912	11.63166	7.829221
		(20.3058)	(16.7992)	(12.2893)
7	7.005537	80.3954	11.73785	7.866752
		(20.7464)	(16.7673)	(12.7803)
8	7.006793	80.38305	11.74974	7.867208
		(21.518)	(17.4184)	(13.1568)
9	7.020052	80.42036	11.74195	7.837688
		(21.9271)	(17.528)	(13.7234)
10	7.021825	80.40224	11.74819	7.84957
		(22.6527)	(17.8485)	(13.9751)

Note: The "Period" column in the table refers to the number of periods of the shock response, based on annual data, with the corresponding time unit being years. It is used to measure the long-term impact path of shocks to various variables on fluctuations in carbon emissions (D_CO_2).

Table 12

D_IC VARIANCE DECOMPOSITION RESULTS				
Variance decomposition of D_IC	**S.E.**	**Impulse variable**		
Period		**D_CO_2**	**D_IC**	**D_ISV**
1	0.110016	8.299040	91.70096	0.000000
		(14.3184)	(14.3184)	(0.00000)
2	0.149330	49.74821	50.18222	0.069576
		(20.1088)	(18.7221)	(6.68990)
3	0.154342	47.78397	51.49080	0.725224
		(18.3199)	(17.7881)	(10.8330)
4	0.159529	47.06336	52.10206	0.834575
		(19.0140)	(18.2415)	(12.4622)
5	0.162188	48.58652	50.43963	0.973847
		(20.0021)	(18.5880)	(11.9865)
6	0.162355	48.50112	50.41877	1.080115
		(20.7425)	(18.9032)	(12.3260)
7	0.163149	48.73675	50.16575	1.097506
		(20.8170)	(18.8475)	(12.2659)
8	0.163329	48.78757	50.08776	1.124661
		(21.4879)	(19.5020)	(12.5976)
9	0.163350	48.78574	50.08221	1.132046
		(22.1658)	(20.1215)	(12.8542)
10	0.163473	48.85127	50.01820	1.130523
		(22.1684)	(19.8518)	(13.4974)

Note: The "Period" column in the table refers to the number of periods of the shock response, based on annual data, with the corresponding time unit being years. It is used to measure the long-term impact path of shocks to various variables on fluctuations in carbon emissions (D_IC).

Table 13

D_ISV VARIANCE DECOMPOSITION RESULTS				
Variance decomposition of D_ISV	**S.E.**	**Impulse variable**		
Period		**D_CO_2**	**D_IC**	**D_ISV**
1	1493.128	2.136105	4.901384	92.96251
		(9.33651)	(10.5468)	(13.4570)
2	1540.186	3.248214	8.338625	88.41316
		(12.0231)	(13.8982)	(17.1046)
3	1610.899	3.531391	9.545294	86.92332
		(14.8295)	(14.1346)	(17.6680)
4	1638.745	6.437920	9.352284	84.20980
		(14.3905)	(13.7021)	(17.5514)
5	1658.238	6.510335	11.08701	82.40265
		(15.2935)	(13.6011)	(17.6320)
6	1663.681	6.786963	11.34843	81.86461
		(16.6154)	(14.9340)	(18.3993)
7	1669.947	7.284392	11.45047	81.26514
		(17.0572)	(15.6468)	(18.8581)
8	1671.848	7.285457	11.62085	81.09369
		(17.5922)	(15.4319)	(18.9874)
9	1672.150	7.293589	11.62562	81.08079
		(17.9480)	(15.8213)	(19.1523)
10	1672.394	7.315762	11.62709	81.05715
		(19.4131)	(16.3587)	(19.7653)

Note: The "Period" column in the table refers to the number of periods of the shock response, based on annual data, with the corresponding time unit being years. It is used to measure the long-term impact path of shocks to various variables on fluctuations in carbon emissions (D_ISV).

itself remained stable at 50.02% – 50.42%, whilst D_ISV remained below 1.13%. Monte Carlo standard errors demonstrated that the uncertainty of estimates was relatively small (such as the Period 10 standard error for D_CO_2 being 18.31%), further supporting the dominant role of both D_CO_2 and D_IC's own shocks in D_IC fluctuations.

Table 13 revealed that the variance decomposition of D_ISV demonstrated self-shock centrality with gradually emerging D_IC influence. The forecast error variance of D_ISV was primarily explained by its own shocks, whilst D_IC's influence strengthened gradually over time and stabilised, with D_CO_2's influence remaining relatively weak.

Short-term (Period 1): D_ISV itself explained 92.96% of the forecast error variance, with D_IC explaining 4.90% and D_CO_2 explaining 2.14%, indicating that short-term fluctuations were dominated by self-shocks.

Medium-term (Periods 2–5): D_ISV's own explanation proportion declined from 88.41% in Period 2 to 82.40% in Period 5. D_IC's explanation proportion increased from 8.34% to 11.09%, whilst D_CO_2's explanation proportion rose from 3.25% to 6.51%. This indicated that the impacts of D_IC and D_CO_2 shocks on D_ISV gradually emerged, with D_IC's influence being more significant.

Long-term (Periods 6–10): The explanation proportions of all variables converged to stability: D_ISV itself maintained 81.27% – 81.86%, D_IC stabilised between 11.35% – 11.63%, and D_CO_2 stabilised between 6.79% – 7.32%. Monte Carlo standard errors demonstrated that the uncertainty of estimation results was relatively low (such as the Period 10 standard error for D_IC being 16.33%), validating the robustness of long-term dynamic relationships.

CONCLUSIONS, IMPLICATIONS AND OUTLOOK

Research conclusions

This study examined the relationships between economic growth, industrial concentration, and carbon emissions in the textile industry through Granger causality testing, VAR model lag determination, cointegration testing, VAR impulse response, and variance decomposition methods, yielding the following conclusions:

(1) VAR Granger Causality Test Results: At the 5% significance level, only the textile industry carbon emission change rate (D_CO_2) constituted a Granger cause of the industrial concentration change rate (D_IC) (Chi-sq = 11.426, P = 0.0033), whilst no significant Granger causal relationships existed among other variables. Specifically, D_IC and the economic growth change rate (D_ISV) did not constitute Granger causes of D_CO_2 (P-values of 0.3779 and 0.4841, respectively); D_ISV did not constitute a Granger cause of D_IC (P=0.8222); and D_CO_2 and D_IC did not constitute Granger causes of D_ISV (P-values of 0.5691 and 0.6374, respectively).

Overall, Granger causal relationships between variables were weak, with only D_CO_2 exerting a significant influence on D_IC.

(2) Unrestricted Cointegration Rank Test (Trace): At the 5% significance level, one cointegrating equation existed. Normalised cointegrating coefficients indicated that the long-term equilibrium relationship was: D_CO_2 + 23.61231D_IC – 0.001343D_ISV = 0 (with standard errors of 20.2206 for D_IC and 0.00133 for D_ISV), demonstrating stable long-term associations among the three variables, with D_IC exhibiting relatively significant influence.

(3) Impulse Response Analysis: Variable shocks demonstrated differential impacts on various series. D_CO_2's own shocks exhibited evident responses in early periods, whilst D_IC shocks had transient effects on it; D_IC demonstrated positive impulses to D_CO_2 shocks, with weak self-shock influences; D_ISV exhibited sustained responses to D_CO_2 shocks, with substantial self-shock volatility. Overall, dynamic interactions existed between variables, with D_CO_2 playing a relatively prominent role in transmission mechanisms, providing foundations for understanding variable relationships and subsequent analysis.

(4) Variance Decomposition Analysis: D_CO_2 shocks possessed significant explanatory power for D_IC (approximately 48.85% in the long term), whilst D_IC's influence on D_CO_2 remained weak (approximately 11.75% in the long term); D_IC's influence on D_ISV (approximately 11.63% in the long term) exceeded D_CO_2's influence on D_ISV (approximately 7.32% in the long term). Among the three variables, the forecast error variance of D_CO_2 and D_ISV was primarily explained by their own shocks in the long term (approximately 80.40% and 81.06%, respectively), whilst D_IC was jointly dominated by its own shocks and D_CO_2 shocks (approximately 50% each). The explanation proportions of all variables stabilised after Period 5, indicating that the system achieved long-term equilibrium, with dynamic influence relationships between variables converging to stable states.

Research implications

(1) Focus on Core Causality and Strengthen the Guiding Role of Carbon Emissions on Industrial Concentration. Given that only D_CO_2 constituted a significant Granger cause of D_IC, the formulation of synergistic "carbon emission constraints – industrial concentration optimisation" policies was recommended. For high-carbon emission enterprises in the textile industry, measures such as dynamic carbon quota adjustments and green technology subsidies could compel enterprise mergers, reorganisations, or technological collaboration, promoting industrial concentration aligned with low-carbon development requirements. The establishment of dynamic monitoring mechanisms for carbon emissions and industrial oncentration was suggested to evaluate the transmission effects of D_CO_2 shocks on D_IC in real-time and optimise policy tool combinations accordingly.

(2) Anchor Long-term Equilibrium and Construct Multi-variable Synergistic Regulatory Framework. Based on the cointegration test's revelation of "long-term stable associations among D_CO_2, D_IC, and D_ISV," the construction of cross-variable synergistic regulatory systems was required. Using cointegrating equations as constraints, long-term adaptation targets for textile industry carbon emissions, industrial concentration, and economic growth (or scale variables) needed to be established. For variables deviating from equilibrium, differentiated policy interventions (such as implementing industry subsidies or production restrictions for D_IC deviations) could guide the system back to long-term stable states.

(3) Optimise Dynamic Interactions and Design Precise Short-term Shock Response Strategies. Combining the "differential characteristics of variable shocks" revealed by impulse response analysis, differentiated short-term regulatory measures should have been implemented. Targeting D_CO_2's "strong early-period response" to its own shocks, carbon market emergency adjustment mechanisms (such as short-term carbon price fluctuations and reserve quota releases) needed to be established to smooth short-term violent carbon emission fluctuations. Utilising the "positive impulse effect" of D_CO_2 on D_IC, industry integration policies (such as specialised merger and acquisition funds) could have been launched synchronously during carbon emission shock periods, accelerating industrial concentration optimisation through low-carbon constraints. Attention to D_ISV's "high volatility characteristics" in self-shocks required counter-cyclical regulation of textile industry scale variables (such as output value and capacity) through measures like short-term credit support and capacity warnings to weaken system disturbances.

(4) Stabilise System Equilibrium and Establish Long-term Dynamic Monitoring and Adjustment Mechanisms. Based on the variance decomposition conclusion that "variable explanation proportions stabilised after Period 5", long-term equilibrium maintenance mechanisms needed to be constructed. Systematic assessments should have been conducted at 5-period intervals to monitor changes in variance explanation proportions of D_CO_2, D_IC, and D_ISV, with timely policy intensity adjustments (such as strengthening green technology R&D investment when D_CO_2's self-explanation proportion remained persistently high, reducing carbon emission inertial dependence). Dynamic updating mechanisms for policy toolboxes needed to be established, flexibly switching between carbon taxes, industry subsidies, and scale controls based on variable equilibrium states to ensure long-term stable system convergence.

Through the aforementioned policy designs, the variable relationship characteristics revealed by research could have been effectively connected, forming closed loops from short-term shock responses to long-term equilibrium maintenance, facilitating the textile industry's achievement of synergistic goals of "low-carbon development – industrial optimisation – economic stability."

Research outlook

This study, through systematic analysis, clarified the existence of dynamic associations between carbon emissions, industrial concentration, and economic growth in the textile industry, providing a foundational framework for understanding the intrinsic logic of industry development and low-carbon transformation. However, as the textile industry constituted a complex industry characterised by extensive industrial chains, significant regional differences, and strong policy sensitivity, numerous deeper patterns in the interactive mechanisms between variables remained to be explored. Future research could have been further deepened from three aspects to enhance the practical guidance value of the conclusions.

Firstly, focusing on industry subdivisions to thoroughly analyse heterogeneous characteristics of variable relationships. Current research predominantly employed the textile industry as a whole as the analytical unit, but spinning, weaving, dyeing, and garment processing subsectors demonstrated significant differences in energy consumption, carbon emission intensity, market concentration, and economic contribution. For example, the dyeing sector, as a high-energy consumption and high-emission core sector, might have exhibited entirely different relationships between carbon emissions and industrial concentration compared to the low-emission garment processing sector – the former might have achieved scale-based emission reduction effects through increased concentration, whilst the latter might have experienced dispersed emissions that were difficult to control due to small and medium enterprise clustering. Through disaggregating subsectors, unique association patterns among carbon emissions, concentration, and economic growth within each sector could have been precisely identified. For instance, the technology-intensive attributes of the spinning sector might have resulted in strong positive correlations between concentration increases and economic growth, with carbon emissions being more influenced by technological upgrades; the dyeing sector's strong policy constraints might have made the balance between carbon emissions and economic growth more dependent on pollution treatment facility sharing following concentration increases. Such subdivision research could have provided precise foundations for differentiated policy formulation, avoiding "one-size-fits-all" regulatory approaches and making policy interventions more aligned with the actual development needs of each sector.

Secondly, introducing cutting-edge analytical methods to explore non-linear and dynamic time-varying characteristics between variables. Existing research predominantly constructed models based on linear assumptions, whilst during the textile industry's development process, relationships among carbon emissions, concentration, and economic growth might have exhibited non-linear characteristics following technological breakthroughs, policy shocks, and market structure changes. For example, when industrial concentration crossed certain thresholds, scale effects might have caused carbon emission intensity to demonstrate cliff-like declines rather than linear growth; economic growth's pulling elasticity on carbon emissions during different stages (such as high-speed expansion periods versus high-quality development periods) might also have exhibited structural breaks. Introducing machine learning methods (such as LASSO regression) could have precisely screened key moderating factors affecting relationships from high-dimensional variables (such as environmental technology investment and carbon trading policies), identifying turning points in non-linear relationships. Dynamic Bayesian VAR models could have captured evolutionary trajectories of inter-variable relationships over time, revealing changes in association strength during different periods (such as environmental policy tightening periods and industrial transfer peak periods), thereby improving model fitting precision to real-world scenarios. These methodological innovations could have not only enriched theoretical analytical frameworks but also provided more scientific tool support for predicting industry development trends and formulating dynamic adjustment policies.

Thirdly, expanding cross-regional research perspectives to analyse spatial transmission mechanisms and policy synergistic effects under industrial transfer backgrounds. Industrial transfer in the textile industry (such as migration from eastern to central and western regions) might have led to spatial redistribution of carbon emissions, whilst inter-regional economic associations (such as industrial chain supporting and trade exchanges) could have created spatial spillover effects in the influences of concentration and economic growth. For example, increased industrial concentration in eastern regions might have driven emission reductions in central and western regions through technological spillovers, whilst low environmental costs in central and western regions might have attracted high-emission capacity transfers, forming "pollution haven" effects.

Constructing spatial VAR models could have quantified such spatial transmission intensity, identifying interactive pathways of carbon emissions and concentration between regions. Combined with Dynamic Stochastic General Equilibrium (DSGE) models, the implementation effects of multiple policy combinations, such as carbon taxes, industry subsidies, and regional collaborative emission reductions, could have been simulated, evaluating costs and benefits of different policy tools in cross-regional coordination. Such cross-regional research could have not only filled current gaps in regional heterogeneity analysis but also provided theoretical support for formulating collaborative policies that balanced regional equity with overall benefits, facilitating deep coordination between low-carbon development and high-quality growth in the textile industry nationwide.

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Cashmere, silk and wool blended woven fabrics: an investigation of physical and handle properties

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ABSTRACT – REZUMAT

Cashmere, silk and wool blended woven fabrics: an investigation of physical and handle properties

This study investigates the physical, mechanical, and handle properties of woven fabrics produced using various luxury animal fibres, including 100% cashmere, superfine wool, wool/silk (70/30), and cashmere/silk (70/30) blends. All fabrics were woven under identical construction conditions, with only the weft yarn composition varying. Comprehensive testing, covering breaking strength, tear resistance, seam slippage, dimensional stability, elongation, air permeability, and bending rigidity, was conducted before and after finishing processes. Results showed that 100% cashmere fabrics exhibited the highest breaking strength, while wool/silk blends offered comparable performance with significant cost advantages. Coarser wool yarns (21.5 µm) provided superior tear strength, whereas silk blends enhanced elongation and resilience. Wool/silk fabrics also demonstrated the best seam slippage resistance and the highest air permeability. Cashmere and silk-containing fabrics, though softer and more drapable, showed greater dimensional shrinkage after finishing. Statistical analysis revealed that fabric properties were significantly influenced by weft yarn composition (p<0.05), with finishing treatments affecting elongation, permeability, and rigidity. Notably, wool/silk (70/30) fabrics emerged as the most balanced option, combining mechanical performance, tactile comfort, and economic feasibility. These findings highlight the potential of superfine wool and silk blends as viable alternatives to cashmere in premium textile applications.

Keywords: *cashmere, wool, silk, woven fabrics, fabric performance, handle, yarn blend*

Țesături din amestec de cașmir, mătase și lână: o analiză a proprietăților fizice și tactile

Prezentul studiu analizează proprietățile fizice, mecanice și tactile ale țesăturilor realizate din diverse fibre animale de lux, inclusiv cașmir 100%, lână superfină, amestecuri de lână/mătase (70/30) și cașmir/mătase (70/30). Toate țesăturile au fost obținute în condiții identice de fabricație, variind doar compoziția firului de bătătură. Au fost efectuate teste cuprinzătoare care au acoperit rezistența la rupere, rezistența la sfâșiere, alunecarea cusăturii, stabilitatea dimensională, alungirea, permeabilitatea la aer și rigiditatea la îndoire, înainte și după procesele de finisare. Rezultatele au arătat că țesăturile din 100% cașmir au prezentat cea mai mare rezistență la rupere, în timp ce amestecurile de lână/mătase au oferit performanțe comparabile cu avantaje semnificative din punct de vedere al costurilor. Firele de lână mai groase (21,5 µm) au oferit o rezistență superioară la rupere, în timp ce amestecurile cu mătase au îmbunătățit alungirea și reziliența. Țesăturile din lână/mătase au demonstrat, de asemenea, cea mai bună rezistență la alunecarea cusăturilor și cea mai mare permeabilitate la aer. Țesăturile care conțin cașmir și mătase, deși mai moi și cu o drapabilitate mai bună, au prezentat o contracție dimensională mai mare după finisare. Analiza statistică a relevat că proprietățile țesăturilor au fost influențate semnificativ de compoziția firelor de bătătură (p<0,05), tratamentele de finisare afectând alungirea, permeabilitatea și rigiditatea. În mod deosebit, țesăturile din lână/mătase (70/30) s-au evidențiat ca fiind opțiunea cea mai echilibrată, combinând performanța mecanică, confortul tactil și fezabilitatea economică. Aceste descoperiri evidențiază potențialul amestecurilor de lână superfină și mătase ca alternative viabile la cașmir în aplicațiile textile de lux.

Cuvinte-cheie*: cașmir, lână, mătase, țesături, proprietățile țesăturilor, textură, amestec de fire*

INTRODUCTION

The use of luxury animal fibres in textiles, such as cashmere, silk, and wool, plays a crucial role in improving the aesthetic appeal, tactile comfort, and thermal insulation of high-end garments. These fibres, known for their softness, luster, and breathability, are commonly used in premium segments of the fashion industry [1, 2].

Cashmere, obtained from the undercoat of Capra hircus laniger goats native to the Himalayan and Central Asian regions, is especially prized for its exceptional softness, fine diameter (often <16.5 µm), and limited global availability, estimated at just 16,000 tons annually [3]. However, its extremely high market price (up to €219/kg) poses challenges for large-scale industrial use, prompting researchers and manufacturers to explore more cost-effective alternatives that maintain similar tactile and performance qualities [4].

Silk, derived from the cocoon of the Bombyx mori silkworm, offers a combination of high tensile strength, elongation capacity, and a smooth hand feel due to its long filament structure [5, 6]. Its inclusion in blends often enhances softness and reduces pilling, while maintaining good mechanical strength [7].

Wool, especially superfine wool with diameters around 15.5 μm, is another potential substitute for cashmere. It provides elasticity, warmth, and natural resilience. Moreover, it is more readily available and less costly than cashmere, especially when sourced from well-established sheep breeds [8, 9].

Due to increasing consumer expectations, cost pressures, and sustainability concerns, textile manufacturers are increasingly exploring fibre blends to strike a balance between luxury, performance, and economic feasibility [10]. Blending wool and silk or using superfine wool offers a way to emulate the luxurious hand of cashmere while reducing dependency on rare and expensive fibres.

Previous studies have extensively investigated the influence of animal fibres on yarn and fabric properties, especially in the context of luxury applications. For instance, McGregor and Naebe evaluated the tactile characteristics of knitted fabrics made from superfine wool and cashmere blends, showing that increasing cashmere content improved softness and elasticity but also raised production costs [11]. Similarly, Supüren Mengüç compared the physical performance of various animal/viscose blended yarns and emphasised the contribution of silk and angora to comfort properties such as warmth and hand feel [7]. In another study, Gürkan Ünal et al. (2019) explored the substitution of wool with alpaca and silk in woven fabric weft yarns, concluding that silk inclusion altered dye uptake and air permeability while enhancing tactile properties [12]. Atav, Ergünay, and Gürkan Ünal developed a methodology to accurately distinguish between yak and cashmere fibres using microscopic and spectroscopic analyses, aiming to prevent mislabelling in textile products [13]. Gürkan Ünal, Atav, and Ergünay evaluated the permeability and tactile handle properties of hand-knitted fabrics made from wool, yak, and cashmere fibres, highlighting significant differences across materials with respect to breathability and fabric hand characteristics [14].

However, most of these studies focus either on knitted structures or on yarn-level comparisons without isolating the effects of weft composition in woven fabrics under consistent manufacturing parameters. Moreover, there remains a lack of comprehensive investigation that compares 100% cashmere fabrics with superfine wool and wool/silk blends across a full spectrum of performance parameters, such as tensile strength, pilling, dimensional stability, air permeability, and tactile response, in a woven fabric context.

This study aims to examine the effects of various animal fibre blends, specifically 100% cashmere, cashmere/silk, wool/silk, and superfine wool, on the physical, mechanical, and tactile properties of woven fabrics. By holding production parameters constant (weave type, warp yarn, finishing treatments), the influence of weft fibre composition is isolated and quantitatively evaluated. This study seeks to answer a key industrial question: Can silk or superfine wool blends replicate the premium qualities of cashmere while significantly reducing cost?

Ultimately, this research contributes to the technical literature on luxury textiles and provides practical guidance for manufacturers aiming to optimise performance-to-cost ratios in high-end fabric collections.

MATERIALS AND METHOD

This study focused on woven fabrics produced with various luxury and semi-luxury animal fibre blends, using 100% wool yarns in the warp and differing yarn compositions in the weft. The weft yarns used include:

- 100% cashmere
- 70% cashmere / 30% silk
- 70% wool / 30% silk
- 100% wool with varying fibre diameters (15.5 μm, 18.5 μm, 21.5 μm)
- 100% wool yarns produced via both conventional and Siro-spinning methods.

All weft yarns were spun to a fineness of Nm 60/2. Fabric construction was kept constant using a plain weave, uniform warp yarns, and consistent production parameters. This uniformity allowed for an isolated evaluation of how different weft yarn compositions influenced the resulting fabric properties. The produced fabrics were summarised in table 1. The fabrics in question were washed at only 60°C and then dried in a stenter machine at 100°C at a speed of 25 m/min.

The experimental workflow involved three major stages: characterisation of fibres, yarn testing, and evaluation of fabric performance using industry-standard methods.

Fibre Length was measured with the Almetre AL-100 according to the IWTO 17-85 E standard, which employs electrostatic variation to detect fibre lengths. Each measurement was conducted three times [15]. Fibre Fineness was determined using the micro-projection method based on ASTM D2130. This approach evaluates the average diameter from cross-sections of fibre bundles under magnification, taking 400 samples per test [16]. Fibre Tenacity was evaluated using the Presley tester. The Presley Index (P.I.) was calculated and converted to cN/tex using standard formulas. Performance was classified according to industry scales for wool fibre strength [5].

After fibre conditioning, yarns were produced using both conventional ring spinning and siro-spinning (for selected samples). Supplier-sourced yarns (for silk and cashmere) were evaluated for quality assurance. Yarn tests included:

Count (Nm) was measured using the skein method in accordance with TS 244 EN ISO 2060. Twist (T/m) was determined via the Mesdan Twist Tester using the untwist-retwist method (TS 247 EN ISO 2061). Tensile strength and elongation tests were conducted on Uster Tensorapid 3 under TS EN ISO 2062 conditions. Yarn evenness and hairiness tests were analysed with Uster Tester 4. Imperfections such as thin places (–50%), thick places (+50%), and neps (+200%) were reported per 1000 m. Hairiness Index

FABRIC WEAVING DETAILS							
Fabric composition	100% Wool	100% Wool	100% Wool	100% Wool	50% Cashmere	35% Cashmere	85% Wool
					50% Wool	50% Wool	
	15.5 µm	18.5 µm	21.5 µm	21.5 µm siro		15% Silk	15% Silk
Warp Yarn	Nm 60/2 Double Plied 100% Wool 21.5 µm 750 T/m S Twisted Conventional Production						
Reed No	100/2						
Weft Yarn	Nm 60/2						
	100% Wool	100% Wool	100% Wool	100% Wool	100% Cashmere	70% Cashmere	70% Wool
						30% İpek	30% Silk
	15.5 µm	18.5 µm	21.5 µm	21.5 µm	15.5 µm	15.5 µm	15.5 µm
	Conv.	Conv.	Conv.	Siro	Conv.	Conv.	Conv.
Weft Density	20 picks/cm						
End fabric (g/m^2)	142.5	149.5	151.5	152	152	150	164.5
Width of end fabric (cm)	144	141.5	145	144.5	144.5	144.5	143

(S3) was quantified by surface fibre length per unit yarn length.

All fabrics were woven on Dornier looms using a plain weave structure and the same warp setup. Finishing included a 60°C washing followed by drying at 100°C using a stenter at 25 m/min. The conditioned fabrics under standard laboratory conditions were subjected to the following standardised tests: fabric mass per unit area was measured according to TS 251 using circular fabric samples and a precision scale. Tensile strength in the weft direction was applied according to TS EN 13934-1 to determine maximum breaking force and elongation using CRE testers. Tear strength in the weft direction was assessed using ISO 13937-2 with adapted jaws on the same tensile tester. Seam slippage resistance was conducted via the fixed seam opening method to measure displacement under a 200 N force. The Hoffman shrinkage test was applied to estimate dimensional stability under steam and pressure using Hoffman pressing equipment. Elongation and residual elongation tests were measured under load and after relaxation, according to Dupont TTM 075 A procedure. Air Permeability was measured over a 20 cm² area at 100 Pa using the Prowhite Airtest II in compliance with TS 391 EN ISO 9237. Bending Rigidity of the fabrics was calculated using Shirley Stiffness following the BS 3356 cantilever method, a reliable indicator of fabric softness and flexibility.

Data were analysed using the General Linear Model (GLM) to determine the significance of fibre type and finishing effects on dependent variables. Where ANOVA revealed statistical differences ($p<0.05$), Tukey's post-hoc test was employed to identify group differences. This ensured rigorous evaluation of performance trends among fibre compositions.

RESULTS AND DISCUSSION

This section presents and interprets the physical, mechanical, and comfort-related performance results of fabrics produced with different weft yarns composed of wool, silk, and cashmere in various proportions. All fabrics were woven under constant construction parameters, which enabled the attribution of performance differences directly to fibre content and yarn structure.

The physical characterisation of fibres used in this study revealed clear distinctions in fineness, length, and short fibre content across wool, cashmere, and silk. These inherent differences critically influence the spinnability and quality attributes of the resulting yarns. Table 2 presents the average measurements for fibre fineness, staple length, and proportion of short fibres (<30 mm) in the raw materials used.

The following key observations were made:

- Silk fibres had the finest and longest structure (11.12 µm, 80 mm), making them ideal for producing smooth, lustrous yarns with low hairiness and high tensile strength.
- Cashmere fibres, although finer than wool, had much shorter lengths (~45 mm) and higher short fibre content (~25%), which negatively impacted yarn evenness and hairiness.
- Superfine wool (15.5 µm) offered a promising compromise: low micron value, moderate-to-high staple length (~70 mm), and low short fibre percentage, making it a viable alternative to cashmere in terms of hand feel and yarn performance.
- Coarser wool fibres (18.5 µm and 21.5 µm) provided better cohesion and strength due to longer average fibre length, with the lowest proportion of short fibres (down to 9.7%).

These findings support the assertion that fibre morphology, particularly fineness and length, is a primary determinant of yarn and fabric performance [1,7]. While cashmere delivers unmatched softness, superfine wool and wool/silk blends offer technically viable and economically attractive alternatives.

When the fibre and yarn analysis results presented in table 3 are evaluated together, it is clearly seen that

Table 2

SUMMARY OF FIBRE PROPERTIES				
Yarn type	Fibre	Fineness (m)	Length (mm)	Short fibre percentage (<30 mm) (%)
100% Wool 15.5 μm	Wool	15.3	70	9.1
100% Wool 18.5 μm	Wool	18.3	66.4	13.3
100% Wool 21.5 μm	Wool	21.4	79.5	9.7
100% Wool 21.5 μm	Wool	21.3	79.5	9.7
100% Cashmere	Cashmere	15.86	45	26.7
70% Cashmere-30% Silk	Cashmere	15.7	46	24.5
	Silk	11.12	80	7.8
70% Wool-30% Silk	Wool	15.5	70	9.1
	Silk	11.12	80	7.8

Table 3

YARN TEST RESULTS											
Fibre	**Form**	**Nm**	**CV (%)**	**Twist (T/m)**	**Evenness (%)**	**Tenacity (cN/tex)**	**Elongation (%)**	**Thin places –50%**	**Thick places 50%**	**Neps 200%**	**Hairiness S3**
Wool 15.5 μm Conv.	Package	59.40	1.80	845	14.50	4.10	8.00	658.00	48.50	18.50	731
	Plied	33.00	1.60	681	8.00	9.17	22.00	0.00	2.50	12.50	334
Wool 18.5 μm Conv.	Package	61.44	2.87	734	15.12	7.23	15.95	572.50	99.50	168.50	1002
	Plied	30.54	1.97	754	9.57	9.01	18.42	2.00	4.00	5.00	644
Wool 21.5 μm Conv.	Package	58.99	1.80	704	16.30	6.67	17.80	714.50	134.50	212.00	1706
	Plied	29.00	2.00	719	10.40	9.14	28.10	3.50	2.00	5.00	1143
Wool 21.5 μm Siro	Package	30.05	1.00	661	10.90	9.26	24.91	16.50	2.00	3.00	1180
Cashmere Conv.	Package	61.30	2.67	798	12.40	7.97	11.00	62.50	38.00	24.00	1031
	Plied	30.70	1.10	758	8.10	9.49	23.00	0.00	5.00	3.80	763
Cashmere/ Silk Conv.	Package	60.10	1.21	704	10.70	13.58	8.00	5.50	8.50	15.00	852
	Plied	29.30	0.50	753	6.70	14.59	10.00	0.00	0.00	2.50	650
Wool/Silk Conv.	Package	55.45	0.63	545	9.57	14.53	9.00	1.00	2.00	12.50	324
	Plied	26.45	1.10	523	6.60	13.30	13.00	0.00	0.00	0.00	324

fibre properties directly reflect on yarn performance. Silk and superfine wool fibres, which stand out in terms of fibre fineness and length, provide advantages in yarn production with their low irregularity and high elongation values. Especially after the doubling process, yarns produced from wool fibres with a fineness of 15.5 μm stand out with their low hairiness (S3: 334) and high specific strength (9.17 cN/tex), while it was observed that the elongation rate was around (22%). On the other hand, in cashmere yarns with a high short fibre ratio, irregularity values (8.10%) and hairiness (S3: 763) were obtained after doubling. In the measurements made in the bobbin form of the cashmere yarns in question, the irregularity values and hairiness values are quite higher compared to the values of yarns produced from superfine wool fibres. This can be associated with the fly and interrupted fibre distribution arising from the short structure of the fibre. In addition, when the cashmere/silk blended yarns were examined, a homogeneous structure due to the mixture was obtained; After winding and folding, the unevenness is 10.70% and 6.70 and the hairiness is 852–650, respectively. Here, it shows that the long and fine structure of the silk balances the short fibre structure of the cashmere. In wool/silk blended yarns, comfortable and smooth-surfaced yarns were obtained with low twist, low hairiness (S3: 324) and good elongation (13.0%). On the other hand, in yarns produced with 21.5 μm thick wool fibres, the hairiness and unevenness values increase significantly (S3: 1706), and this increase becomes more pronounced, especially in the siro spinning method. Folding with the conventional method offers an advantage in terms of

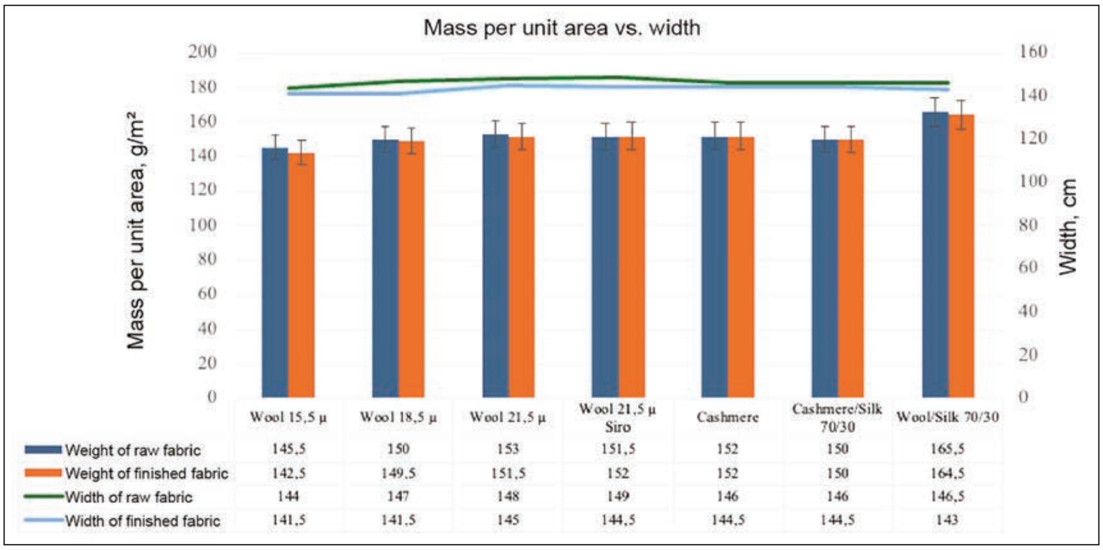

Fig. 1. Results of mass per unit area and width of the fabrics produced with different weft yarns

hairiness compared to the siro method. As a result, yarn quality increases as the fibre length and fineness increase; especially superfine wool and silk blends offer strong alternatives that can replace cashmere in terms of both production performance and fabric comfort.

The results of mass per unit area and width of the fabrics woven with different weft yarns before and after finishing processes are presented in figure 1. All grey fabrics (before finishing) exhibited similar weights, ranging from approximately 145.5 g/m² (15.5 µm wool) to 165.5 g/m² (wool/silk 70/30 blend). After finishing, fabric weights slightly decreased due to mechanical relaxation and moisture loss during washing and drying, consistent with expectations in textile finishing [17]. The wool/silk 70/30 blend showed the highest final mass (164.5 g/m²), which may be attributed to the silk's high density and the coarser yarn count used in that blend.

Based on the results of the statistical analysis, fabric mass per unit area is significantly affected only by the type of weft yarn used ($p<0.05$). The observed difference is primarily attributed to the fabric woven with wool/silk (70/30) blended weft yarn, which exhibited the highest fabric weight among all groups. This finding indicates that fibre type plays a decisive role in determining the final mass per unit area of the fabric. Fabrics produced from wool/silk blends resulted in significantly higher mass values, whereas those made from pure wool and cashmere showed comparatively lower weights.

The differences between the grey (unfinished) and finished fabric weights can be explained by moisture loss and dimensional shrinkage occurring during the stenter drying process. However, this post-finishing variation was found to be less influential than the type of fibre used in the weft composition.

As shown in figure 2 in the left-hand chart, breaking strength values in the weft direction varied significantly across fibre types. The highest breaking strength was observed in fabrics woven with 100% cashmere (52.25 kgf in finished form), followed closely by the wool/silk 70/30 blend (54.4 kgf). This indicates that both cashmere and silk-rich blends contribute positively to tensile performance, likely due to their elastic and cohesive fibre structures.

Conversely, fabrics produced from finer and coarser pure wool yarns (15.5 µm and 18.5 µm) exhibited significantly lower breaking strengths (around 25–28 kgf), suggesting that wool alone, regardless of fibre fineness, does not achieve the same level of tensile performance. The increase in strength after finishing observed in all samples can be attributed to fibre

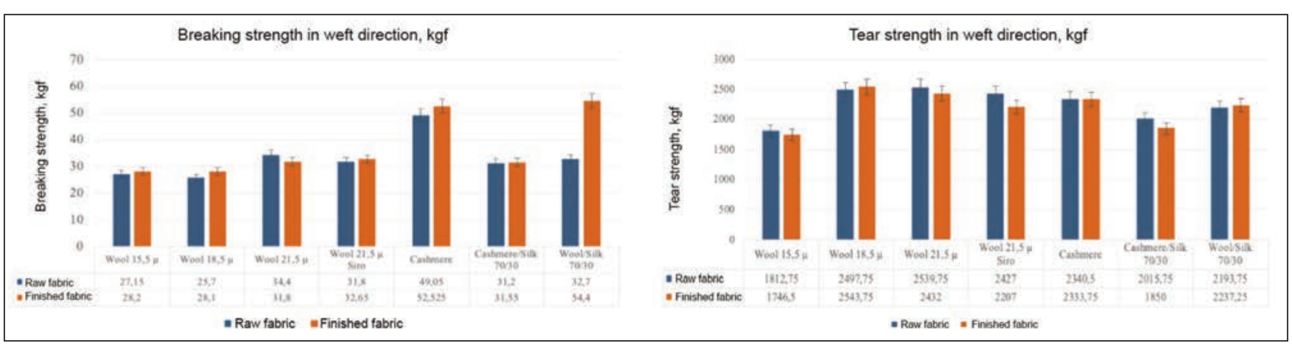

Fig. 2. Results of breaking strength and tear strength in the weft directions of the fabrics produced with different weft yarns

consolidation and residual shrinkage that increases fabric compactness.

As a result of the statistical analysis, the fabric weft direction breaking strength is affected by both the weft yarn used and the processes it undergoes after the raw material ($p<0.05$). The effect of using different fibres in the weft yarn on the fabric strength in the weft direction has caused the formation of three classes according to the Tukey pairwise comparison analysis results: cashmere (A)> wool/silk (B) > cashmere/silk (C)-wool (C). The Tukey pairwise comparison results, which were made to see the difference between the raw and finished product, are as follows: finished product (A) > raw (B), and there is a statistically significant difference between the two averages. As a result, when the fibre structure, yarn quality and fabric construction are evaluated together, it is concluded that the woven fabrics produced using 100% cashmere fibres in the weft yarns show high performance in terms of breaking strength in the weft direction; however, the woven fabrics produced using wool/silk blended weft yarns also stand out as a cost-effective and high-strength alternative.

The right-hand chart illustrates tear strength in the weft direction for both grey and finished fabrics. In general, coarser wool fabrics (21.5 μm) showed the highest tear resistance (finished fabric: 2534.75 gf), followed by the wool/silk 70/30 blend (2237.25 gf) and wool 21.5 μm siro yarns (2402 gf). Tear strength is primarily influenced by the yarn's ability to resist sudden localised force, which is enhanced in coarser and more cohesive fibre structures. Notably, cashmere/silk blends and 100% cashmere fabrics demonstrated comparatively lower tear strengths (1859–2333 gf), indicating that despite their softness, they are more vulnerable to sudden rupture. The post-finishing reduction in tear strength across most fabrics may result from reduced extensibility and increased fabric rigidity due to shrinkage and heat exposure during processing. As a result of the GLM analysis, the tear strength of the fabric in the weft direction is affected only by the weft yarn used ($p<0.05$), and the difference between raw and finished fabrics is insignificant. The effect of using different fibres in the weft yarn on the tear strength of the fabric in the weft direction has caused the formation of two classes according to the Tukey pairwise comparison analysis results: cashmere (A) > wool (A) > wool/silk (A,B) > cashmere/silk (B). Accordingly, the differences between cashmere and cashmere/silk, wool and cashmere/silk are statistically significant.

Figure 3 the chart on the left presents seam slippage values in the weft direction for both raw and finished fabrics. Across all samples, finishing slightly reduced seam slippage resistance due to fabric relaxation and shrinkage-induced density increases. The highest seam slippage was recorded in wool/silk 70/30 blend fabrics, with values reaching 20 kgf after finishing, suggesting superior inter-fibre cohesion and yarn strength in this blend. In contrast, cashmere fabrics displayed the lowest resistance to seam opening (14.9 kgf finished), which can be associated with the smooth and slippery surface of short, fine fibres, whereas higher hairiness generally increases friction and thus can improve seam slippage resistance. All fabrics exceeded the minimum seam strength requirement (12 kgf) for quality garment applications, but silk-containing blends consistently outperformed pure wool and cashmere samples.

As a result of the statistical analysis, the fabric seam slippage is affected only by the weft yarn used ($p<0.05$). The effect of using different fibres in the weft yarn on the fabric seam opening strength in the weft direction has caused the formation of two classes according to the Tukey pairwise comparison analysis results: wool/silk (A) > cashmere/silk (A, B) > wool (B) > cashmere (B). Accordingly, the differences between wool/silk and wool, wool/silk and cashmere are statistically significant. The difference between raw and finished fabrics is insignificant.

In figure 3, the right-hand chart shows the results of the Hoffman press test, which measures dimensional change under steam and pressure. All fabric types exhibited a greater negative dimensional change (shrinkage) after finishing compared to their raw states. While raw fabrics showed shrinkage values around –0.3% to –0.5%, finished fabrics reached –1.0% across all samples, indicating typical relaxation and structural tightening during finishing. Notably, no significant differences in shrinkage behaviour were observed between fibre types, suggesting that the finishing process itself (especially stenter drying and compression) was the primary contributor to dimensional reduction, rather than fibre composition. These findings align with prior research

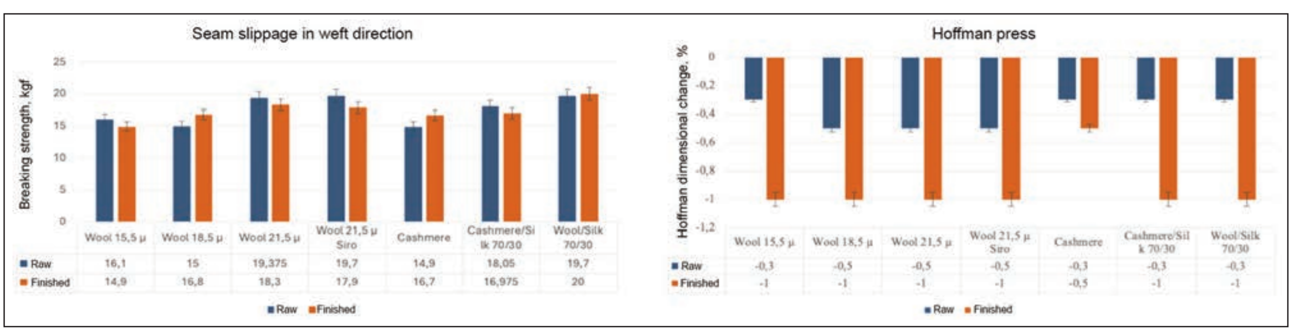

Fig. 3. Results of seam slippage in the weft direction and dimensional change under the Hoffman press

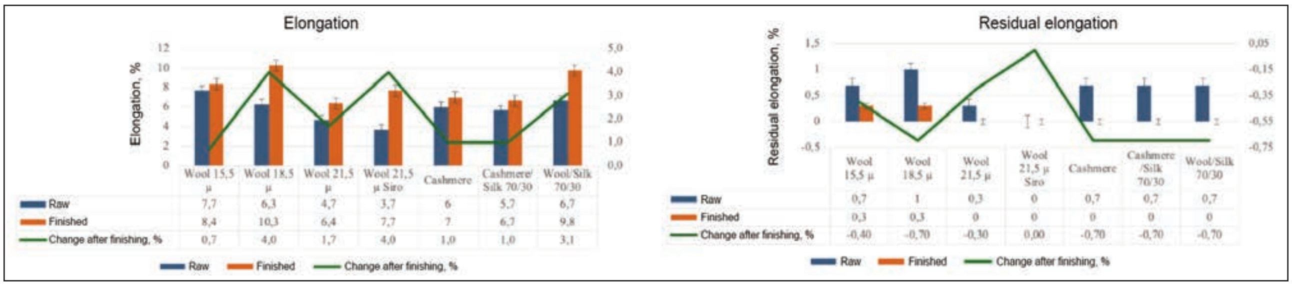

Fig. 4. Results of elongation and residual elongation of the fabrics produced with different weft yarns

emphasising the dominant role of mechanical processing over fibre morphology in determining steam-induced dimensional change.

As a result of the statistical analysis, Hoffman press results are affected by both the weft yarn used and the post-raw processes ($p<0.05$). The effect of using different fibres in the weft yarn on dimensional change behaviour has caused the formation of two classes according to the Tukey pairwise comparison analysis results: cashmere (A) > wool/silk (B) > cashmere/silk (B) > wool (B). The Tukey pairwise comparison results, which were made to see the difference between raw and finished, are as follows: raw (A) > finished (B), and there is a statistically significant difference between the two means.

Figure 4 illustrates the elongation and residual elongation behaviour of fabrics in raw and finished states. Across all fabric types, finishing processes led to a notable increase in elongation, with the most prominent change observed in wool 18.5 µm fabrics, which increased from 6.3% to 10.3% (a 4.0% gain). This increase can be attributed to the relaxation of internal yarn tensions and structural compactness introduced during finishing. Overall, wool/silk 70/30 and cashmere fabrics exhibited moderate elongation improvements (3.1% and 1.0%, respectively), indicating that silk-containing blends not only maintained but enhanced their elasticity after finishing. This outcome is favourable for applications requiring both dimensional resilience and wearer comfort.

The chart on the right shows residual elongation, which represents the permanent deformation remaining after a load is removed. All fabrics experienced a decrease in residual elongation after finishing, suggesting improved elastic recovery. For example, wool 15.5 µm and wool 21.5 µm fabrics showed a 0.4% and 0.3% reduction, respectively. Importantly, the wool 21.5 µm siro yarn fabrics exhibited no residual elongation in either state, highlighting the benefits of sirospun yarn structure in resisting plastic deformation. Silk-containing fabrics also demonstrated a significant reduction (–0.7%), confirming silk's role in enhancing fabric resilience. These results underline the effectiveness of finishing in promoting structural elasticity and minimizing permanent set, crucial for high-performance woven garments.

In figure 5, the left-hand chart displays the air permeability results of raw and finished fabrics. Overall, finishing caused a slight reduction in air permeability across all samples, attributed to increased fabric density due to relaxation shrinkage. The highest air permeability was observed in wool 21.5 µm siro yarn fabrics (518.2 L/m²·s raw, 501.4 finished), followed by wool/silk 70/30 blends, indicating that both siro spinning and silk inclusion contribute to a more open fabric structure. In contrast, cashmere fabrics and cashmere/silk blends exhibited the lowest permeability values (around 250–270 L/m²·s), likely due to their higher surface fuzz and compactness. These results suggest that fibre fineness, yarn structure, and blend composition are key determinants of breathability. As a result of the statistical analysis, fabric air permeability is affected by both the weft yarn used and the processes it undergoes after raw ($p<0.05$). The effect of using different fibres in the weft yarn on fabric air permeability has caused the formation of two classes according to the Tukey pairwise comparison analysis results: Wool/silk (A) > wool(A) > cashmere/silk(B) > cashmere (B). The Tukey pairwise comparison results, which were made to see the difference between raw and finished, are as follows: Raw (A) >

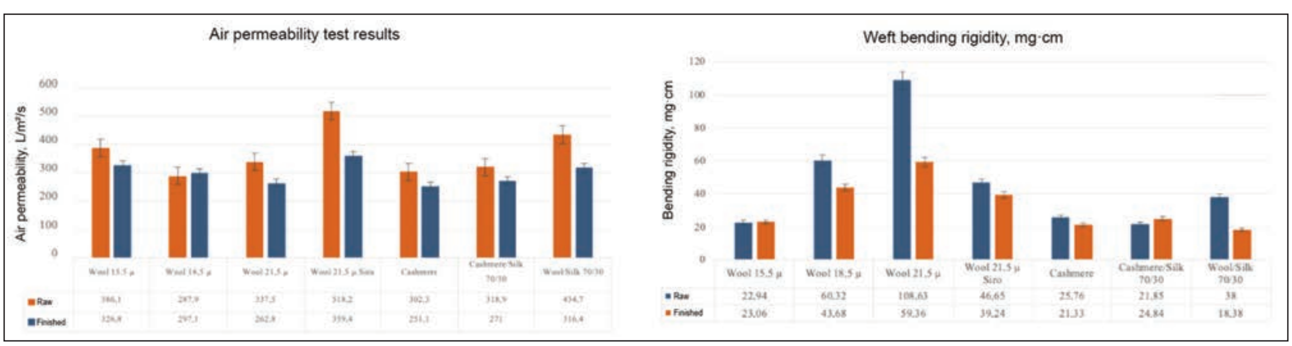

Fig. 5. Results of air permeability and weft bending rigidity of the fabrics produced with different weft yarns

finished (B), and there is a statistically significant difference between the two means.

Air permeability is significantly affected by both fibre type and finished process. While siro yarns, silk-blended wool fabrics and more open weave structures provide advantages in performance textiles requiring high permeability, denser, shorter-fibred and high-hairiness yarn structures (e.g. cashmere) limit permeability. It was observed that the finished processes reduced the permeability in almost all groups, and this was attributed to the tightening of the porosity structure of the fabric during the process.

In figure 5, the right-hand chart presents bending rigidity in the weft direction, which reflects the stiffness and drape characteristics of the fabric. A significant decrease in bending rigidity was observed after finishing for all fabrics. The highest raw rigidity was recorded in wool 21.5 μm fabrics (108.6 mg·cm), which dropped to 59.36 mg·cm after finishing, highlighting the strong impact of wet and thermal processing on stiffness. Cashmere and wool/silk 70/30 fabrics had the lowest bending rigidity values in both raw and finished states, confirming their soft, drapable character. These findings indicate that fibre fineness and finishing processes strongly influence the tactile feel and mechanical behaviour of luxury fabrics, which is crucial for their end-use performance in apparel. As a result of the statistical analysis, the weft direction fabric bending strength is affected by the weft yarn used ($p<0.05$). The effect of using different fibres in the weft yarn on the weft direction fabric bending strength has caused the formation of two classes according to the Tukey pairwise comparison analysis results: Wool (A) > wool/silk (A > cashmere (B) ≈ > cashmere/silk (B). Weft direction bending strength varies significantly with the effect of fibre thickness, yarn form and especially the processed structure. While wool fibres provide high bending strength as they form a more rigid structure, cashmere and silk added fabrics stand out with their softer handle and lower bending strength. The finished processes have reduced the bending strength in all fabric groups and influence increasing the drape and comfort of use of the fabric.

CONCLUSION

This study comprehensively evaluated the influence of luxury animal fibre compositions, namely cashmere, silk, and wool, on the physical, mechanical, and tactile properties of woven fabrics. All samples were produced under identical construction parameters, enabling a focused assessment of weft yarn variation. The primary aim was to determine whether more affordable fibre blends could serve as effective alternatives to high-cost cashmere without compromising fabric quality and user comfort.

Key findings from the experimental results include:

- Yarn quality: superfine wool (15.5 μm) and wool/silk 70/30 blends demonstrated superior tenacity and low hairiness compared to cashmere yarns, which showed high unevenness due to their shorter fibre length. The inclusion of silk substantially improved yarn strength and surface regularity.
- Fabric strength and durability: while 100% cashmere fabrics exhibited the highest breaking strength, wool/silk blends provided comparable results. Tear strength was highest in coarse wool fabrics and wool/silk combinations, affirming the structural advantage of longer and thicker fibres.
- Pilling resistance: coarse wool fabrics displayed the best resistance to pilling. Cashmere and cashmere/silk blends performed poorly due to their short fibre lengths and higher surface fuzz. Silk additions slightly mitigated pilling, but not sufficiently to match the wool-based alternatives.
- Seam slippage and stability: wool/silk blends achieved the highest seam strength, while cashmere-containing fabrics were more prone to slippage. All fabrics showed improved dimensional stability post-finishing, though cashmere and silk blends exhibited more shrinkage due to their hygroscopic nature.
- Air permeability and handle: wool/silk and siro-spun wool fabrics offered high breathability, suitable for comfort-driven applications. In contrast, cashmere blends produced denser fabrics, ideal for winter wear. Bending rigidity results showed that cashmere and silk significantly enhanced softness and drapability, while wool contributed to fabric firmness and structure.
- Cost-to-performance analysis: while 100% cashmere delivers premium tactile and thermal qualities, its market price limits its scalability. Wool/silk 70/30 blends emerged as the most promising substitute, offering high tensile and tear strength, good pilling and seam performance and excellent air permeability and comfort.

This blend provides a compelling balance of luxury, functionality, and affordability.

Additionally, conventional 21.5 μm wool yarns (at only €7/kg) presented an optimal solution for lower-budget collections where mechanical durability and acceptable comfort are prioritised over luxury softness.

This research thus supports the strategic substitution of cashmere with superfine wool and wool/silk blends in fabric engineering. These alternatives not only reduce costs but also offer strong performance in key areas of mechanical durability, comfort, and appearance. The findings have valuable implications for sustainable fabric sourcing, luxury textile innovation, and high-value product development.

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Deep learning-based recognition of Miao ethnic costumes via YOLOv5s: A step toward digital cultural preservation

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ABSTRACT – REZUMAT

Deep learning-based recognition of Miao ethnic costumes via YOLOv5s: A step toward digital cultural preservation

Miao ethnic costumes, celebrated for rich diversity, intricate craftsmanship, and distinctive patterns, represent an important aspect of China's cultural heritage and the broader realm of intangible cultural heritage. In response to the growing need for digital preservation, this study proposes a deep learning-based approach to recognise and document Miao costumes effectively. While traditional costume recognition methods face challenges such as high computational costs and limited analytical capacity, the YOLOv5s framework offers automatic feature extraction and improved scalability. However, its standard form struggles to adequately focus on critical visual features, reducing recognition performance accuracy. To overcome this, we introduce the YOLOv5s-SED model, which incorporates a Squeeze-and-Excitation (SE) attention mechanism and Deformable convolution (DCNv2) into YOLOv5s to enhance feature representation and improve the recognition of fine details. A dedicated dataset of 4,468 annotated images was compiled, and the model was refined through hyperparameter tuning and comparative experiments. The results demonstrate notable performance gains, with precision increasing from 97.1% to 97.6%, recall from 99.3% to 99.8%, and mean Average Precision (mAP) from 70.7% to 71.5%. These outcomes highlight the model's strong generalisation ability in complex environments and its potential to support the digital preservation and promotion of Miao ethnic costumes.

Keywords: *Miao ethnic costumes, cultural heritage preservation, deep learning, YOLOv5s-SED, image recognition*

Recunoașterea costumelor tradiționale Miao pe baza învățării aprofundate prin intermediul YOLOv5s: un pas către conservarea culturală digitală

Costumele tradiționale Miao, apreciate pentru diversitatea bogată, măiestria complexă și modelele distinctive, reprezintă un aspect important al patrimoniului cultural al Chinei și al patrimoniului cultural imaterial în sens larg. Ca răspuns la nevoia tot mai mare de conservare digitală, acest studiu propune o abordare bazată pe învățarea aprofundată pentru recunoașterea și documentarea eficientă a costumelor Miao. În timp ce metodele tradiționale de recunoaștere a costumelor se confruntă cu provocări precum costurile de calcul ridicate și capacitatea analitică limitată, cadrul YOLOv5s oferă extragerea automată a caracteristicilor și o scalabilitate îmbunătățită. Cu toate acestea, forma sa standard se confruntă cu dificultăți în a se concentra adecvat asupra caracteristicilor vizuale critice, reducând precizia performanței de recunoaștere. Pentru a depăși această problemă, a fost introdus modelul YOLOv5s-SED, care încorporează un mecanism de atenție Squeeze-and-Excitation (SE) și convoluție deformabilă (DCNv2) în YOLOv5s pentru a îmbunătăți reprezentarea caracteristicilor și recunoașterea detaliilor fine. A fost compilat un set de date dedicat de 4.468 de imagini adnotate, iar modelul a fost perfecționat prin reglarea hiperparametrilor și experimente comparative. Rezultatele demonstrează îmbunătățiri notabile ale performanței, precizia crescând de la 97,1% la 97,6%, recall-ul de la 99,3% la 99,8%, iar precizia medie (mAP) de la 70,7% la 71,5%. Aceste rezultate evidențiază puternica capacitate de generalizare a modelului în medii complexe și potențialul său de a sprijini conservarea digitală și promovarea costumelor tradiționale Miao.

Cuvinte-cheie: *costume tradiționale Miao, conservarea patrimoniului cultural, învățare aprofundată YOLOv5s-SED, recunoașterea imaginilor*

INTRODUCTION

The Miao ethnic group, one of China's most ancient and culturally significant minorities, is predominantly distributed across Guizhou, Yunnan, Hunan, and neighbouring regions. Renowned for its intricate silver ornaments and vibrant costumes, it serves as a vital component of China's intangible cultural heritage and a symbolic representation of global cultural diversity. Miao ethnic costumes not only encapsulate the essence of the Miao people's "non-written civilisation", but also function as living testimonies to human cultural diversity [1]. Through distinctive material forms, these costumes reflect the ethnic group's historical memory, cosmological beliefs, and spiritual traditions, where specific patterns such as butterfly motifs symbolise ancestral spirits, and dragon designs represent water deities. This fusion of history, philosophy, and artisanal craftsmanship positions Miao costumes as essential carriers of the Miao cultural DNA [2]. Therefore, their preservation value extends beyond the material realm, encapsulating the spiritual continuity of civilisation.

Indeed, Miao ethnic costumes, renowned for their distinctive materials, intricate techniques, and symbolic patterns, offer rich artistic expression and play an essential role in Chinese cultural and artistic traditions [3]. However, the Miao population's sub-tribal divisions and dispersed geographical distribution have resulted in a highly heterogeneous costume system [4]. Although this cultural diversity enhances their value, it also presents significant challenges to systematic protection. Traditional manual classification and visual recognition methods demonstrate inefficiency and poor generalisation [5].

Consequently, developing efficient and accurate recognition methods is crucial for the digital preservation and transmission of Miao costumes. More importantly, these methods fail to decode the semantic relationships between visual patterns and their cultural meanings, a gap our model aims to bridge by linking convolutional feature maps to symbolic annotations in the dataset [6].

With the advancement of intelligent recognition technologies, deep learning has emerged as a promising tool for automatically extracting visual features (e.g., texture, shape, colour) and integrating them with classification or recognition algorithms [4, 7, 8]. Traditional image processing and feature-based methods, such as Scale-Invariant Feature Transform (SIFT), Local Binary Patterns (LBP), and Gabor filter-based texture analysis, have been widely used in textile pattern recognition. However, these approaches rely on manually designed low-level features and fail to capture the deep cultural semantics embedded in symbolic motifs such as butterflies and dragons. Consequently, they offer shallow feature representation and limited interpretability. Moreover, conventional methods show poor adaptability to complex visual scenarios involving garment folds, silver ornament occlusion, and intricate embroidery, while variations in illumination, fabric deformation, and colour-layered structures further reduce their robustness. Despite advances in computer vision for textile inspection and fashion analytics, existing recognition systems still struggle to handle the visual and semantic complexity of traditional ethnic costumes. Most industrial frameworks remain optimised for standardised modern textiles and are thus incapable of interpreting the rich textures and symbolic ornamentation characteristic of heritage garments, creating a persistent gap in the digital documentation and intelligent management of cultural textiles within museums and heritage institutions.

YOLOv5s, as an advanced deep learning-based costume recognition framework, provides an effective solution for Miao costume recognition [9]. Compared to traditional methods, this architecture automatically extracts key garment features through end-to-end learning, with its convolutional neural network capturing high-level semantic characteristics including embroidery patterns, symmetrical designs, and silver ornament arrangements our implementation, visual features are aligned with ethnographic studies (e.g., tribal-specific pattern dictionaries) via a post-processing knowledge graph, establishing a bidirectional pipeline connecting visual recognition with cultural decoding. The framework also demonstrates high efficiency, robust spatial perception, and adaptability to small datasets, enabling better performance in complex scenes [10]. Additionally, the model supports techniques such as transfer learning and data augmentation, helping alleviate data scarcity in the domain of ethnic costume recognition.

However, despite its demonstrated advantages, YOLOv5s exhibits notable limitations in both feature channel selection and local detail representation when processing Miao costume imagery [11]. Specifically, the architecture's lack of an explicit attention mechanism results in suboptimal extraction of fine-grained details – particularly embroidery stitches and localised ornamental elements which serve as critical visual identifiers for accurate cultural recognition. A representative case involves the model's tendency to misclassify spiritually significant motifs such as the "fish-scale pattern" (a traditional symbol representing fertility in Miao culture) as generic texture artefacts when lacking specialised enhancement [12]. While the lightweight design confers computational efficiency benefits, this advantage comes at the cost of reduced capability to discern subtle local features under challenging conditions, including partial occlusion and fabric deformation [13]. Furthermore, constraints imposed by limited training dataset availability and inconsistent image quality frequently lead to either underfitting or overfitting scenarios, thereby substantially compromising the model's generalisation capacity. Overall, these identified limitations collectively impede the practical deployment of YOLOv5s for intangible cultural heritage costumes recognition applications, highlighting the urgent need for both architectural refinements and training protocol optimisations [14].

In response to these limitations, this study presents an enhanced deep learning model for high-precision Miao ethnic costume recognition. Specifically, our approach innovatively integrates the Squeeze-and-Excitation (SE) attention mechanism and Deformable Convolution v2 (DCNv2) into the YOLOv5s backbone network, achieving superior recognition accuracy and robustness. On one hand, the SE module dynamically models inter-channel dependencies, allowing the model to focus on culturally significant features and improve channel-wise feature representation. The SE-generated channel weights highlight convolutional filters activated by culturally diagnostic patterns (e.g., zigzag stitches encoding migration routes), effectively transforming low-level pixels into interpretable cultural symbols [14, 15]. On the other hand, DCNv2 substantially improves spatial adaptability by learning dynamic sampling locations that adjust according to object deformation and geometric variations, demonstrating exceptional performance in challenging scenarios involving fabric folds and ornament occlusion [16]. This capability proves crucial to maintaining semantic integrity, ensuring that culturally important but distorted motifs (e.g., partially obscured "sunburst" patterns representing divinity) are correctly interpreted as complete symbolic units. The synergistic combination of these modules enhances both channel-wise feature representation and spatial feature extraction, delivering significant performance gains without compromising the model's real-time processing capability, thereby advancing digital heritage preservation methodologies.

To summarise, this study addresses key limitations in YOLOv5s –- insufficient feature extraction, weak local expression, and data scarcity – through an optimised framework integrating Squeeze-and-Excitation (SE) attention and Deformable Convolution v2 (DCNv2) modules. The enhanced model improves feature learning across both channel and spatial dimensions, significantly boosting recognition accuracy, robustness, and generalisation in complex environments. In addition to improving recognition accuracy, the proposed framework addresses the pressing need for efficient digital archiving of traditional textiles. Accurate costume recognition facilitates the categorisation, storage, and retrieval of cultural garments in digital databases, supporting long-term textile conservation and cultural heritage digitisation. By linking intelligent recognition technology with textile documentation, the study provides a technical foundation for sustainable cultural preservation. Crucially, it also establishes a technical bridge between computer vision and ethnography by enabling direct mapping between the model's attention heatmaps and cultural symbolism, such as high-attention regions corresponding to totemic patterns. This provides researchers with an effective tool for rapid annotation and interpretation of costume heritage while reducing reliance on large-scale, high-quality datasets. The framework offers a robust technical foundation for intelligently preserving and revitalising traditional ethnic cultures, successfully balancing accuracy with efficiency. Its promising potential extends to broader applications in multi-ethnic costume recognition and digital heritage systems.

Innovations of this study include:

1. To address limited datasets and poor image quality, images of Miao ethnic costumes were collected via web crawlers and search engines, then annotated using LabelImg. A dataset of 4,468 images and annotations was constructed.

2. To improve recognition robustness and generalisation in complex scenarios, the YOLOv5s model was enhanced by incorporating the SE attention module and DCNv2 operator, improving the model's ability to learn inter-channel correlations and enhancing recognition accuracy.

3. Comparative experiments were conducted between the original and improved models under identical training and testing conditions. Model hyperparameters and optimisation strategies were adjusted, further improving recognition performance.

In conclusion, this study makes an important contribution to the intelligent recognition and cultural interpretation of Miao ethnic costumes. By integrating SE attention and DCNv2 modules into the YOLOv5s framework, it effectively enhances feature extraction, recognition accuracy, and cultural semantic understanding. The research not only advances technical innovation in ethnic costume recognition but also provides a valuable foundation for the digital preservation and revitalisation of intangible cultural heritage.

METHODOLOGY

Clothing recognition model and its working principle

The YOLOv5s-SED model comprises five core components: the Input module, Backbone, Neck, Head, and Output module, as illustrated in figure 1. Each component plays a specific role in the recognition of

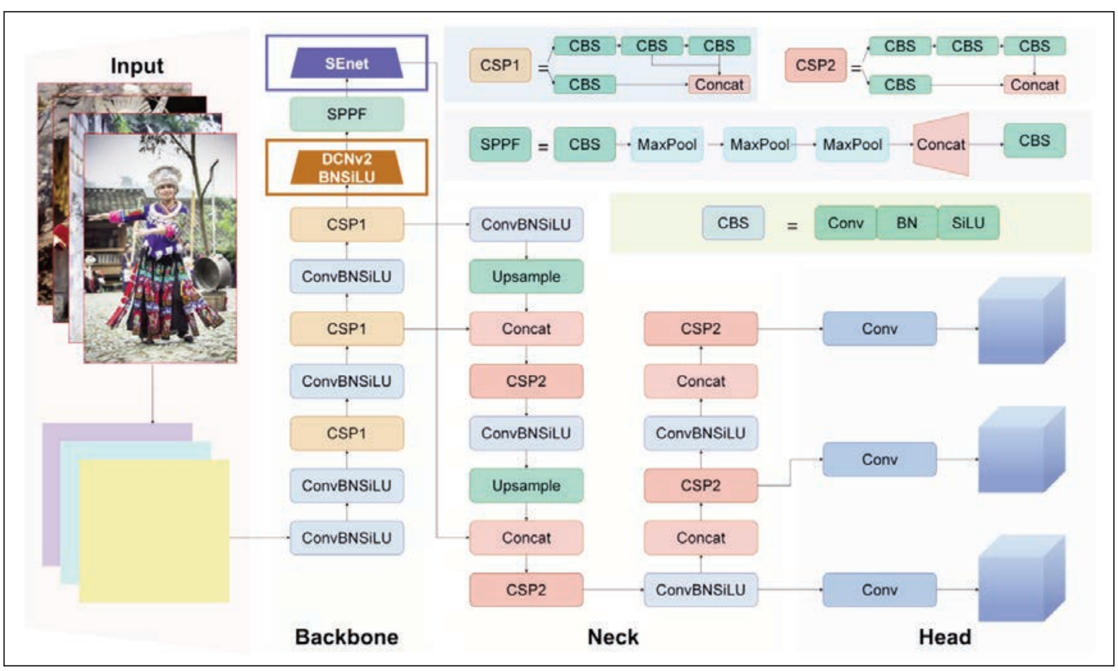

Fig. 1. Structure diagram of the YOLOv5s-SED model

Miao ethnic costumes, from data preprocessing to final output interpretation.

Input module: data augmentation and anchor optimisation

To enhance training data diversity and generalisation, the input stage employs Mosaic data augmentation, which combines four randomly selected images into a single composite input. This approach increases the model's ability to learn under varied lighting conditions, spatial arrangements, and object scales. Additionally, an adaptive anchor box generation strategy is implemented. It uses K-means clustering to align anchor sizes with the actual distribution of costume dimensions in the dataset, improving localisation precision across diverse garment shapes.

Backbone: feature extraction with attention and deformable convolution

The Backbone module extracts structural and semantic features from input images. To improve feature differentiation, a Squeeze-and-Excitation (SE) attention mechanism is embedded in the Spatial Pyramid Pooling-Fast (SPPF) layer. This module models inter-channel relationships, enabling the model to emphasise culturally relevant visual cues, such as embroidery patterns, while minimising background noise.

To handle garment deformation and occlusion, Deformable Convolution v2 (DCNv2) is selectively integrated into the deeper layers of the Backbone. While early layers retain standard convolution to preserve fine details, DCNv2 in later layers enables the model to adapt to non-rigid transformations such as folds or twists in clothing. This targeted design strikes a balance between detailed local feature capture and computational efficiency.

Neck: multi-scale feature fusion

The Neck module performs feature aggregation from multiple levels using a Feature Pyramid Network (FPN). This structure allows the model to maintain semantic consistency across different resolutions and enhances its ability to detect both fine and coarse features typical of Miao ethnic costumes. Through hierarchical fusion, the model adapts better to the scale and complexity of visual patterns.

Head: multi-scale detection

The Head module comprises three parallel detection branches tailored for different object sizes:

1. Small-Scale detection Head identifies distant or intricately detailed costume elements, leveraging high spatial resolution.
2. Medium-Scale detection Head balances resolution and receptive field to detect garments at moderate distances.
3. Large-Scale detection Head targets prominent costume features in close-up views, using broader receptive fields and rich semantic information.

This multi-scale architecture improves detection across varied viewing angles and spatial conditions common in real-world scenarios.

Output module: post-processing and result refinement

In the final stage, Non-Maximum Suppression (NMS) eliminates redundant bounding boxes by selecting only the highest-confidence detections. This results in clean, non-overlapping outputs with precise localisation and labelling of Miao costume components. The final predictions are optimised for accuracy and ready for application in heritage preservation.

SE attention mechanism

The SE attention mechanism refines feature maps by selectively emphasising informative regions. It includes two stages (figure 2).

In the squeeze stage, global average pooling is applied to each feature channel, compressing the spatial information into a single descriptor that reflects the overall importance of that channel. This

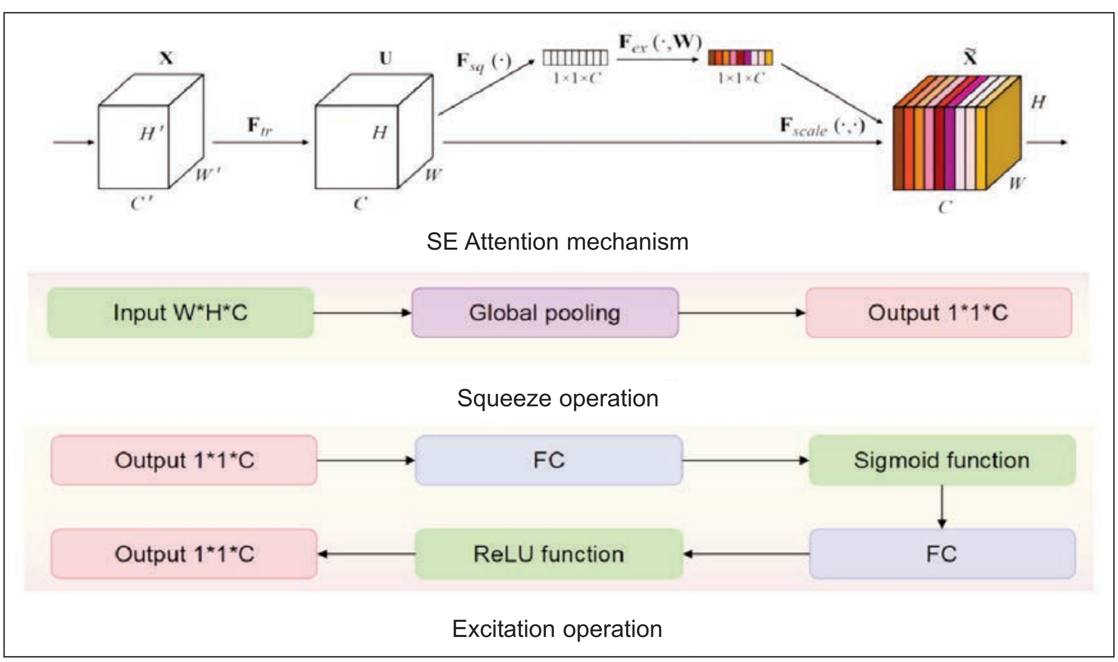

Fig. 2. SE attention mechanism and mechanism analysis

process enables the network to capture the relative significance of each feature channel within the global context. In the excitation stage, these aggregated descriptors are passed through fully connected layers, where non-linear transformations are performed to generate adaptive weights. These weights are then used to re-scale the original feature maps, allowing the model to emphasise informative features while suppressing less important ones, thus enhancing its representational capability [17].

This mechanism helps the model focus on culturally significant costume features, such as embroidery, symbolic motifs, and silver ornaments, while reducing noise from irrelevant background elements.

The process of the SE channel attention mechanism is as follows. Suppose the feature map of the input image X is U, where the dimension of U is $C\times H\times W$, where C is the number of channels, and H and W represent the height and width, respectively [18]. The mapping from the input image to the feature map is according to the following formula:

$$u_c = v_c \times X = \sum_{s=1}^{c'} v_c^s \times X_s \tag{1}$$

Squeeze phase

In the Squeeze operation, to alleviate the problem of channel dependence, the SE module performs global average pooling on the input feature map, uses the output of the previous layer as the input for the current layer, and compresses it into a $1\times 1\times C$ feature vector. The pooled feature vector is denoted as $Z \in R^C$, where Z_c represents the compressed feature of channel c.

$$Z_c = F_{sq}(u_c) = \frac{1}{H\times X}\sum_{i=1}^{H}\sum_{j=1}^{W} u_c(i=j) \tag{2}$$

Excitation stage

To fully leverage the compressed information obtained during the Squeeze operation, the Excitation stage is designed to model the dependencies between feature channels. Its primary goal is to selectively enhance informative features while suppressing irrelevant or redundant ones [19]. This process is implemented using two fully connected (FC) layers that serve as a lightweight gating mechanism, effectively capturing inter-channel relationships.

The output of the Excitation stage is a set of channel-wise attention weights, which are applied to the original feature map via element-wise multiplication [20]. This recalibrates the feature map, amplifying channels that carry semantically meaningful information and attenuating those that contribute less to the recognition task. As a result, the model's attention is directed toward discriminative visual cues, such as intricate embroidery or symbolic motifs, crucial for accurately identifying Miao ethnic costumes in complex backgrounds.

DCNv2 deformable convolution

Deformable convolution differs from standard convolution by introducing learnable offsets at each sampling point within the convolutional kernel [16]. This modification allows the network to adjust its sampling locations dynamically, resulting in a flexible and adaptive receptive field that better captures geometric variations during training. Consequently, the model is able to extract more informative and spatially diverse features from input images, particularly in scenarios involving irregular shapes or deformations common in traditional garments [21].

The following equation represents the output of a standard convolution operation:

$$Y = \sum_{P_n \in R} w(p_n) \cdot x(p_0 + p_n) \tag{3}$$

$$Y = \sum_{P_n \in R} w(p_n) \cdot x(p_0 + p_n + \Delta p_n) \tag{4}$$

As illustrated in figure 3, the incorporation of learnable offsets enables the sampling grid to deviate from the fixed, regular structure of standard convolution. This flexibility allows the model to better align with the contours and structures of irregular costume elements, thereby enhancing its ability to detect fine-grained and contextually significant features [16].

However, this flexibility introduces new challenges. In Deformable Convolution v1 (DCNv1), sampling positions are no longer fixed, which can result in the capture of irrelevant background information [22, 23]. This may dilute the model's focus and interfere with the learning of task-relevant features, particularly when foreground and background elements are closely intertwined.

To mitigate this issue, Deformable Convolution v2 (DCNv2) introduces a critical enhancement: the modulation scalar Δmk for each sampling point. In addition to the learnable offset Δpn, this scalar functions as an attention weight, enabling the network to

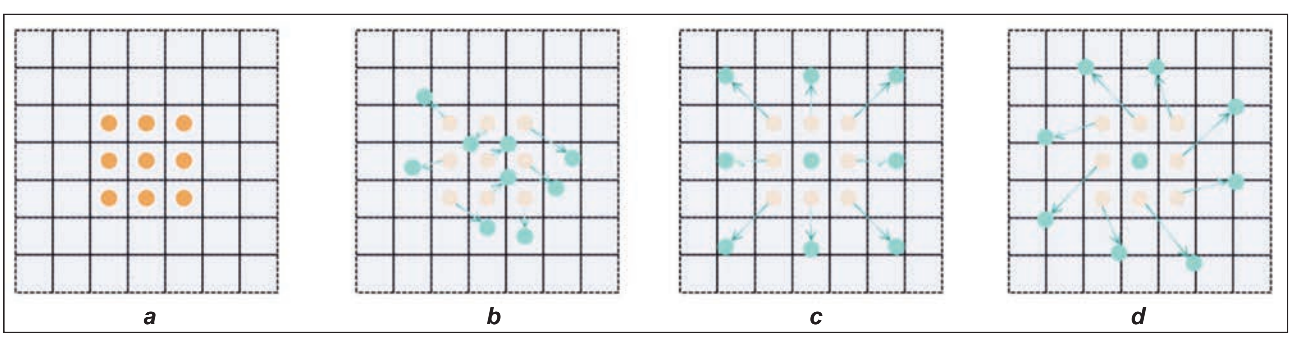

Fig. 3. Ordinary convolution sampling rules and variable convolution sampling rules: *a* – ordinary convolution sampling; *b* – the deformable sampling rule 1; *c* – the deformable sampling rule 2; *d* – the deformable sampling rule 3

emphasise important regions while down-weighting or ignoring irrelevant ones. Specifically, higher weights are assigned to sampling points within regions of interest, while near-zero weights are allocated to areas unrelated to the task, such as background noise. This attention-based refinement significantly enhances the model's ability to distinguish meaningful features from distracting elements in visually complex scenes, leading to more accurate and robust feature representation.

The mathematical formulation of DCNv2 can be expressed as:

$$Y = \sum_{P_n \in R} w(p_n) \cdot x(p_0 + p_n + \Delta p_n) \cdot \Delta m_k \qquad (5)$$

The mathematical formulation of DCNv2 combines both spatial flexibility (via learned offsets) and selective weighting (via modulation scalars), enabling the model to dynamically adapt its focus based on the visual and contextual relevance of each region.

In this study, DCNv2 is incorporated to replace standard convolution in selected layers of the model. This substitution allows for a more complete and precise extraction of costume features, particularly those affected by occlusion, deformation, or variable perspectives. Ultimately, the use of DCNv2 strengthens the model's capacity to recognise Miao ethnic costumes under diverse and challenging visual conditions, enhancing both accuracy and robustness in real-world applications.

Dataset construction and processing

To overcome challenges associated with limited data availability and inconsistent image quality in the recognition of Miao ethnic costumes, this study implements a comprehensive and structured data collection strategy. The process begins with targeted keyword searches, such as "Miao ethnic costumes during festivals" and "details of traditional Miao ethnic costumes"-conducted on major search engines including Baidu and Google. These queries helped form a preliminary image dataset, emphasising authenticity and cultural specificity.

Building upon this foundation, a Python-based web crawler was developed to automate the collection of additional images. This crawler systematically retrieved data from a range of platforms, including websites dedicated to Miao ethnic heritage, traditional clothing e-commerce stores, and social media platforms like Weibo and Douyin. By targeting relevant pages and themes, the crawler extracted image URLs from the HTML structure of each webpage and downloaded the files in batches. Meanwhile, to avoid IP blocking or service denial, request intervals were carefully managed. After image collection, the data was further filtered to ensure quality and compliance. Images with low resolution (below 500×500 pixels), duplicates, or those subject to copyright restrictions were removed to ensure both technical quality and ethical compliance.

To compensate for the limitations of web-acquired data, field investigations were carried out in collaboration with local folk culture institutions. These efforts provided high-resolution photographs of rare and region-specific Miao costumes, captured during on-site visits. This component of the dataset adds valuable depth and authenticity, especially for styles that are underrepresented online.

After completing all image acquisition, a rigorous filtering process was applied to ensure dataset quality and representativeness. Only images that displayed a clear view of Miao ethnic costume features, across diverse body poses, camera angles, and complex background environments, were retained. Images lacking distinctive ethnic characteristics or depicting casual, non-traditional attire were excluded.

During the annotation phase, manual annotation was performed using LabelImg software. Annotators labelled key visual elements, including garment contours, silver ornaments, and embroidery motifs, features essential for accurate model training. Figure 4, *a* presents an overview of the constructed dataset, while figure 4, *b* illustrates the manual annotation process.

a *b*

Fig. 4. Dataset section and annotation process: *a* – the dataset section constructed for this paper; *b* – the manual annotation process using LabelImg

Table 1

DATASET SECTION			
Costume category	**Image count**	**Data source**	**Description**
Ceremonial	1682	Online and field data	Encompasses attire for formal and ritual occasions
Daily	1456	Online and field data	Covers everyday, occupational, and children's attire
Craft-featured	1330	Authorised cultural resources	Features costumes with distinctive embroidery, batik, and silverwork
Total	**4468**	-	-

As a result, a curated and annotated dataset of 4,468 high-quality images was established. This dataset captures rich visual diversity and scene complexity, laying a strong foundation for enhancing the generalisation ability and recognition accuracy of the proposed deep learning-based Miao costume recognition model (table 1).

Experimental design

Ablation study

To identify the optimal integration point for Deformable Convolution v2 (DCNv2), different convolutional layers in the YOLOv5s backbone, already enhanced with the Squeeze-and-Excitation (SE) mechanism, were selectively replaced with DCNv2 layers. Four modified model variants were created, trained on the constructed dataset, and tested on the t1 image. By comparing recognition results across these versions, this experiment determines the most effective layer for incorporating DCNv2. The outcomes also support the theoretical framework discussed earlier in the paper.

Controlled experiment

The model variant that achieved the best performance in the ablation study was designated as YOLOv5s-SED. To thoroughly evaluate its effectiveness, both the baseline YOLOv5s model and the enhanced YOLOv5s-SED model were trained on the same dataset and tested on the t1 image. This direct comparison clearly validates the improvements in recognition accuracy and generalisation brought by the proposed enhancements, specifically in the context of Miao ethnic costume recognition.

Component analysis

To assess the individual impact of each architectural enhancement, two additional model variants were developed by independently incorporating the SE attention mechanism and DCNv2 into the baseline YOLOv5s model. Together with the YOLOv5s and YOLOv5s-SED models, all four versions were trained on the same dataset and evaluated using a representative sample of images. Ultimately, this experiment quantifies the individual and combined contributions of SE and DCNv2 to overall model performance, confirming that the integration of both components yields a significant advantage in complex visual recognition tasks.

RESULTS AND DISCUSSION

Ablation study

In this phase, the deformable convolutional layer DCNv2 was embedded into different layers of the backbone network to evaluate its impact on model performance. Four configurations were tested, each incorporating DCNv2 at progressively deeper layers. These models were designated SE-1, SE-2, SE-3, and SE-4.

Table 2

ABLATION STUDY RESULTS			
Model	**Precision (%)**	**Recall (%)**	**mAP (Mean Average Precision) (%)**
SE-1	97.6	98.9	67
SE-2	96.1	99.6	68.9
SE-3	97.1	99.3	68.2
SE-4	97.1	99.3	70.7

As shown in table 2, the SE-1 model achieves the highest precision (97.6%) on the training set. However, when evaluated on the test image t1, it fails to detect any Miao ethnic costumes (figure 5, *a*), revealing poor generalisation to unseen data. This suggests that placing DCNv2 in early layers disrupts fine-grained feature extraction critical for initial representation learning.

In contrast, SE-2 successfully detects all costume targets in the test image (figure 5, *b*), despite exhibiting slightly lower training precision. SE-3 shows moderate performance; it correctly identifies three costumes but also misclassifies a non-Miao outfit (figure 5, *c*), indicating susceptibility to false positives. SE-4 delivers the best balance between recognition performance and generalisation, achieving the highest mAP (70.7%) and accurately identifying all relevant targets in the test image (figure 5, *d*).

These findings suggest that integrating DCNv2 into the deeper backbone layers optimally enhances the model's spatial adaptability without compromising the integrity of early-stage feature learning. Conversely, introducing it prematurely in the shallow layers undermines recognition robustness.

Controlled experiment

Based on the ablation study, SE-4 was selected as the optimal configuration and named YOLOv5s-SED.

Fig. 5. Recognition results on image t1 using different model variants: *a* – SE-1; *b* – SE-2; *c* – SE-3; *d* – SE-4

Table 3

CONTROLLED EXPERIMENT RESULTS			
Model	**Precision (%)**	**Recall (%)**	**mAP (Mean Average Precision) (%)**
YOLOv5s	97.1	99.3	70.7
YOLOv5s-SED	97.6	99.8	71.5

A controlled experiment was conducted to compare the recognition performance of YOLOv5s-SED against the baseline YOLOv5s model.

As shown in table 3, YOLOv5s-SED surpasses the baseline in all key metrics. While YOLOv5s performs well under most conditions, figure 6, *a* reveals a critical limitation: it misses one of four Miao costumes in a densely packed test image, likely due to occlusion effects. YOLOv5s-SED, by contrast, achieves perfect recognition in the same scenario (figure 6, *b*), confirming its superior spatial reasoning.

Performance over training iterations is shown in figure 7, *b*. YOLOv5s-SED demonstrates a smoother and steeper mAP growth trajectory, converging after approximately 250 epochs with a final mAP of 0.715, an improvement over the baseline's 0.707.

In figure 7, *a*, the shorter the test time for one frame, the better the real-time performance of the model. In

Fig. 6. Recognition results on image t1: *a* – YOLOv5s; *b* – YOLOv5s-SED

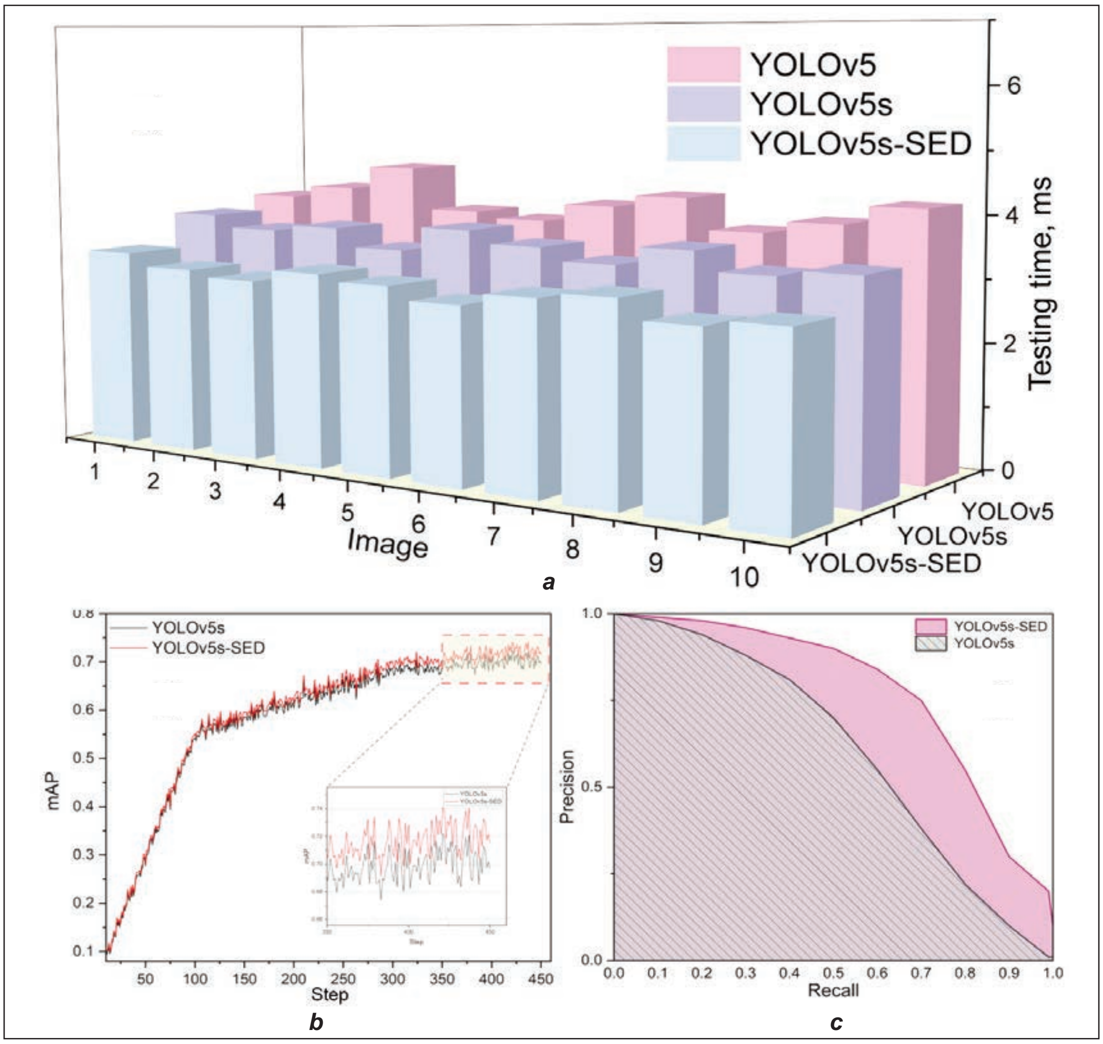

Fig. 7. Graphical representation of: *a* – comparison of experimental recognition speed; *b* – mAP@0.5 curve (the iteration count is scaled up by a factor of 350-450); *c* – comparison of R-P curves

real-time testing using 10 evaluation images, YOLOv5s-SED maintained lower inference latency and more consistent processing times (figure 7, *a*), while retaining a lightweight structure. This highlights its practicality for deployment in live cultural heritage recognition systems.

In figure 7, *c*, the larger the area under the curve, the better the average performance of the model at different thresholds, which also indicates a higher reliability of the model.

Furthermore, the Precision–Recall curve in figure 7, *c* illustrates the robustness of YOLOv5s-SED across classification thresholds. Its larger area under the curve (AUC) compared to YOLOv5s indicates a more reliable balance of precision and recall, with fewer false positives and missed recognitions.

Component analysis

To evaluate the individual contributions of SE attention and DCNv2, two additional variants of the baseline YOLOv5s were constructed, namely YOLOv5s + SE and YOLOv5s + DCNv2.

The baseline YOLOv5s performs reliably in low-complexity environments, showing high confidence and accurate localisation. However, under more challenging conditions, such as cluttered backgrounds or partial occlusion, its performance drops noticeably.

The YOLOv5s + DCNv2 variant demonstrates significantly enhanced recognition robustness, achieving higher IoU values, more stable confidence scores ($p<0.01$), and greater resilience to spatial deformations (figure 8, *b*). These results confirm DCNv2's superior adaptability to geometric variations in costume shapes and poses. In contrast, figure 8, *c* highlights common failure cases, such as missed costume regions and false recognitions on irrelevant backgrounds. This indicates that channel-only attention mechanisms, when lacking spatial modelling, may disrupt the crucial spatial–semantic alignment required for accurate costume recognition.

Table 4

COMPONENT ANALYSIS RESULTS

Model	Precision (%)	Recall (%)	mAP (Mean Average Precision) (%)
YOLOv5s	97.1	99.3	70.7
+DCNv2	96.5	99.8	68.9
+SENet	96.9	99.3	69.2
YOLOv5s-SED	97.6	99.8	71.5

Fig. 8. Recognition results of component models on selected images

By integrating SE and DCNv2, the YOLOv5s-SED model achieves a synergistic enhancement in recognition performance. It effectively balances precision and recall, maintaining consistent accuracy and stability across the dataset. The integrated architecture strengthens both semantic sensitivity and spatial adaptability, making it exceptionally well-suited to the complex visual and structural features of Miao ethnic costumes.

CONCLUSIONS

This study focuses on the recognition of Miao ethnic costumes through deep learning, supported by the construction of a high-quality, annotated dataset comprising 4,468 images. To address the challenges of fine-grained costume recognition, we introduced an enhanced recognition model, YOLOv5s-SED, by incorporating the Squeeze-and-Excitation (SE) attention mechanism and Deformable Convolution v2 (DCNv2) into the YOLOv5s framework. As a result, this integration improves both semantic focus and spatial adaptability, leading to significant gains in recognition performance. The proposed model achieves a precision of 97.6%, a recall of 99.8%, and a mean Average Precision (mAP) of 71.5%, while substantially reducing missed recognitions and improving robustness across complex visual conditions.

However, despite these promising results, the current dataset is primarily composed of female ceremonial costumes, lacking representation of male garments, casual wear, and regional variations within the Miao community. Consequently, this limited diversity affects the model's generalisation capability. Additionally, the computational complexity introduced by the architectural enhancements poses challenges for real-time deployment on resource-constrained devices.

The proposed recognition framework holds significant potential for real-world applications in textile museums, archives, and cultural heritage institutions. By integrating the model into digital documentation workflows, curators and researchers can efficiently catalogue, retrieve, and interpret costume artefacts with high accuracy, thereby enhancing the accessibility and sustainability of textile heritage through intelligent digitisation. Looking ahead, future work will focus on expanding the dataset to encompass a wider variety of costume types, cultural subgroups, and environmental contexts, as well as exploring optimisation strategies such as depth-wise separable convolutions and knowledge distillation to reduce model size and inference latency. Furthermore, potential application directions include the use of augmented reality (AR) for immersive virtual try-on experiences and automated pattern generation for cultural design reproduction. Collectively, these efforts aim to advance the transition from static digital preservation toward dynamic cultural revitalisation, establishing a robust technological foundation for the sustainable safeguarding and innovation of Miao intangible cultural heritage.

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How does supply chain concentration influence the digital transformation-collaborative innovation nexus in the Chinese textile industry?

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AN YU-XIA

ABSTRACT – REZUMAT

How does supply chain concentration influence the digital transformation-collaborative innovation nexus in the Chinese textile industry?

Supply chain concentration, defined as the reliance on a few customers and suppliers, presents both opportunities and risks for firms, particularly when seeking to drive innovation through digital transformation. In the Chinese textile industry, this supply chain concentration could either facilitate or hinder the effectiveness of digital strategies designed to promote collaborative innovation. Realising the economic significance of the Chinese textile industry, this study explains how supply chain concentration influences the relationship between digital transformation and collaborative innovation in the Chinese textile sector. Using data of 942 A-share listed textile firms in China, this study reveals a robust positive relationship between digital transformation and collaborative innovation, demonstrating that digital strategies have the potential to foster innovation in the sector. To address potential endogeneity concerns, we further validate this finding using the two-stage least squares (2SLS) regression model. However, the study uncovers that textile companies operating within highly concentrated supply chains face constraints that prevent them from fully leveraging digital transformation for collaborative innovation. Furthermore, heterogeneity analysis shows that industry-specific factors, such as pollution levels, and firm characteristics, including firm size (FS), significantly moderate this relationship. These findings suggest that policymakers should focus on improving digital infrastructure, promoting financial inclusion, and diversifying supply chains to enable textile firms to more effectively utilise digital transformation for driving collaborative innovation.

Keywords: *digital transformation, collaborative innovation, supply chain concentration*

Cum influențează concentrarea lanțului de aprovizionare legătura dintre transformarea digitală și inovarea colaborativă în industria textilă din China?

Concentrarea lanțului de aprovizionare, definită ca dependența de un număr redus de clienți și furnizori, prezintă atât oportunități, cât și riscuri pentru întreprinderi, în special atunci când acestea urmăresc să stimuleze inovarea prin transformarea digitală. În industria textilă din China, această concentrare a lanțului de aprovizionare ar putea fie să faciliteze, fie să împiedice eficacitatea strategiilor digitale menite să promoveze inovarea colaborativă. Având în vedere importanța economică a industriei textile din China, acest studiu explică modul în care concentrarea lanțului de aprovizionare influențează relația dintre transformarea digitală și inovarea colaborativă în sectorul textil din China. Folosind date de la 942 de întreprinderi textile listate pe piața de acțiuni de tip A din China, acest studiu relevă o relație pozitivă puternică între transformarea digitală și inovarea colaborativă, demonstrând că strategiile digitale au potențialul de a stimula inovarea în acest sector. Pentru a aborda potențialele preocupări legate de endogenitate, a fost validată în continuare această constatare, folosind modelul de regresie cu cele mai mici pătrate în două etape (2SLS). Cu toate acestea, studiul relevă faptul că întreprinderile textile care își desfășoară activitatea în cadrul unor lanțuri de aprovizionare puternic concentrate se confruntă cu constrângeri care le împiedică să valorifice pe deplin transformarea digitală în scopul inovării colaborative. În plus, analiza eterogenității arată că factorii specifici industriei, precum nivelurile de poluare, și caracteristicile întreprinderilor, inclusiv dimensiunea întreprinderii (FS), moderează în mod semnificativ această relație. Aceste concluzii sugerează că factorii de decizie ar trebui să se concentreze pe îmbunătățirea infrastructurii digitale, promovarea incluziunii financiare și diversificarea lanțurilor de aprovizionare, pentru a permite întreprinderilor din sectorul textil să utilizeze mai eficient transformarea digitală în vederea stimulării inovării colaborative.

Cuvinte-cheie*: transformare digitală, inovare colaborativă, concentrarea lanțului de aprovizionare*

INTRODUCTION

Digital transformation has emerged as a cornerstone of the modern world's economic strategy, driving an unprecedented growth of various sectors. China's digital economy accounts for 41.5% of its GDP, reaching a valuation of $7.1 trillions, with enterprises increasingly adopting the technological solutions of artificial intelligence, Internet of Things (IoT), cloud computing, and blockchain to foster operational excellence [1]. The "Broadband China" initiative, launched by the Chinese government in 2014, accelerated China's digital infrastructure investments across various sectors and enabled a cross-regional collaboration and innovation among enterprises [2].

Such investments allowed enterprises to reduce their transaction costs and facilitate real-time data sharing, thus positioning China as a global lead of digital adoption. Researchers argue that enterprises can foster their resilience by boosting market performance through process and product innovation [3]. Consequently, innovations within supply chain networks emerged as a strategic solution for businesses to address both internal and external environmental shifts [4]. As more companies are involved in these innovations, the collaborative networks become more transparent and effective to enable faster decision-making that further helps in adapting to the disruptions and extending the capacity to manage external shocks and risks [5]. During the uncertain times, supply chain innovations allow collaborative networks to rapidly recover by dynamically adjusting their resources, processes, and structures. Therefore, we can claim that collaborative innovation has emerged as a key solution for enterprises to boost their resilience and strengthen their antifragility within collaborative networks [6]. Despite significant progress, Chinese textile enterprises face systemic challenges to leverage digital transformation for collaborative innovations. Essential technologies that support digital transformation remain insufficient [7, 8]. First, High transaction costs, knowledge barriers, and a mismatch of business philosophies hinder cross-regional collaborations, particularly among the small and medium-sized enterprises (SMEs) [7]. Second, the uneven distribution of resources and power creates friction in supply chain collaborations [9]. Third, information overloading from excessive digitalisation risks overwhelming firms, stifling the innovation efficacy of enterprises. Fourth, the structural rigidity in a concentrated supply chain limits the adaptability, as firms are heavily relying on a few partners [10]. Lastly, conflicts of interest and misaligned incentives among supply chain partners impede collaborative innovations. The rapid pace of technological development has exacerbated these issues, which require an agile response that many Chinese firms are struggling to execute [11]. This necessitates an urgent need to identify effective strategies that may help enterprises to achieve effective outcomes from supply chain collaborative networks. However, the lack of standardised digital protocols across industries complicates data sharing, while cybersecurity concerns limit firms from being fully involved in collaborative platforms [12]. Further, regional differences also undermine the trust and cooperation between enterprises, such as firms in Eastern China, with access to advanced digital infrastructure, may hesitate to collaborate with Western China enterprises. These barriers collectively constrain the potential of digital transformation to drive innovation, emphasising the need for strategic interventions to foster a more collaborative ecosystem. Addressing these challenges could be possible through unlocking the full potential of digital transformation.

The rapid advancement and application of cutting-edge information technologies amplify digital empowerment, which plays a crucial role in driving collaborative innovation in the supply chain of textile enterprises. Digitalisation offers essential strategic resources such as data [13], digital platforms [9], and digital thinking frameworks [14] to support supply chain collaborative innovations. Previous studies show that digitalisation fosters automation and intelligence [15], lowers innovation costs [16], and stimulates employees' innovative capacity [14], thereby improving the overall collaborative innovation capabilities and effectiveness. The success of digitalisation can be demonstrated in various business contexts, such as JingDong (JD) automated almost 95% of its inventory processes through a network of digital alliances with various suppliers. Similarly, Nike reduces its labour costs by 50% and raw materials' costs by 20% by leveraging its manufacturers' digital procurement systems. Silva and Gomes [17] find that real-time analytics platforms allowed firms to shorten their R&D cycles by 30%. Digital strategies promote innovative ecosystems, where firms utilise resources through collaborations and mitigate their potential risks [18]. Institutionalising digital workflows allows firms to transcend geographical and organisational boundaries and create a synergistic innovation network. Based on these views, it can be argued that digital transformation unlocks new opportunities for collaborative innovation and drives sustainable growth and competitiveness.

Supply chain concentration (SCC) – relying on a limited number of suppliers/customers – can significantly moderate the nexus of digital transformation with collaborative innovation within the Chinese textile industry. Highly concentrated supply chains benefit from deeper integration, as repeated interactions foster trust and knowledge codification [19]. Using digital tools for co-design enabled a concentrated supplier network of Toyota for rapid prototyping [20]. Conversely, overly concentrated supply chain risks rigidity, as over-reliance on fewer partners can expose the organisation to diverse ideas and business philosophies [10]. Digital platforms can mitigate the supply chain concentration's negative effects by presenting a transparent look at interactions, and thus enabling firms to engage niche suppliers without physical proximity. In this way, supply chain concentration's impact hinges on how firms orchestrate digital tools to optimise partner diversity and depth [21]. For example, firms with moderated supply chain concentration can leverage digital tools to diversify their supplier base while maintaining a strong relationship with key partners, and thus promoting innovation and resilience [22]. Additionally, supply chain concentration influences the distribution of digital resources, with a concentrated supply chain often prioritising investments in core partners, potentially marginalising the smaller players. However, digitalisation can democratize access to resources, ensuring that all partners are equally benefiting from innovative initiatives. This dynamic interplay between supply chain concentration and digital transformation necessitates the importance of strategic partner management to maximise innovative outcomes.

In this context, the rapid growth of the digital economy presents a crucial framework to guide enterprises to enhance supply chain collaborative innovation through digital transformation, and supply chain concentration may influence the digital transformation – innovative nexus. This study aims to examine the nexus between digital transformation, supply chain collaborative innovation, and the moderating role of supply chain concentration. These are the specific research questions answered by this study:

RQ1: How does digital transformation influence the supply chain collaborative innovation in Chinese textile enterprises?

RQ12: How does supply chain concentration (SCC) moderate the nexus between digital transformation and supply chain collaborative innovations?

The remainder of the paper is structured as follows: 2nd section provides a review of relevant literature on key aspects and develops hypotheses; 3rd section outlines research methodology and data; 4th section covers results and discussion of empirical tests, 5th section concludes the paper with theoretical and practical implications.

LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

Digital transformation involves leveraging digital technologies to transform and extend an organisation's business model to alter the value creation capacity of the organisation [23]. This transformation includes corporate strategy, organisational structure, business processes, human resources, and product offerings, all aimed at adapting to dynamic changes in the business environment of an organisation [24]. Some researchers consider digital transformation as a single-dimensional concept [25], while others involve both breadth and depth [15, 26]. Additionally, some scholars focused on specific dimensions of digital transformation, such as capability and strategy. Proksch and Rosin [27] argue that digital strategy significantly influences the digitalisation process of new ventures, and Khin and Ho [28] show that digital capabilities influence corporate performance.

On a global scale, digital strategy catalyses to guide digital transformation and aid firms to integrate, coordinate, and allocate digital resources more effectively [29]. Hess and Matt [30], from a collaboration and integration perspective, state that digital strategy serves as the organisational blueprint which is created and executed to deliver differentiated value by using various digital resources. Managers may use digital technologies for streamlining the operational models both pre- and post-transformation, promoting deeper interactions with customers, suppliers, and competitors. In the face of disruptions, managers are required to establish and execute digital strategies to optimise the company's operational excellence. Digital capability sets the foundation of digital transformation and enables businesses to sense and respond to customers' needs, and also creates a mutually beneficial situation for both companies and their key partners [31].

Supply chain (SC) collaborative innovation is defined as the process of joint research, development, and introduction of new products, services, and processes with partners to boost enterprise competitiveness [32]. This approach helps enterprises enhance innovation capabilities by sharing knowledge with external partners, such as suppliers, customers, competitors, and research organisations [23]. SC collaborative innovation has been widely adopted by companies, with applications in joint procurement, marketing cooperation, and research and development (R&D). This collaboration enables organisations to better handle future crises, significantly improving SC resilience and antifragility.

Supply chain collaboration can be categorised in several way. First, it may be based on the participants involved in a collaborative network, such as suppliers, competitors, customers, and research institutes. Second, supply chain collaborative innovations can be categorised into incremental or radical innovations, depending on the innovative intensity [33]. Third, it can be viewed from the content of innovation, such as a process, product, or management innovation [34]. This study considers collaborative innovation from the perspective of jointly gained patents by Chinese companies through partnerships with suppliers and customers [17, 35]. This perspective involves sharing of technical information and resources with supply chain partners to enhance design, research and development, production, and sales methods. There can be collaboration with suppliers and customers to introduce new products, enter new markets, and diversify the product portfolio to meet the changing customer demands.

Getting basis from strategic choice, it is argued that a company's business strategy must align with the dynamic external environment to remain competitive in the industry. As digitalisation becomes a key business strategy, digital strategy reflects a company's approach of inclusiveness, innovation, growth, and change. Organisations with digital strategies, when compared to those without them, tend to foster entrepreneurial thinking among employees, and enhance their performance to promote process innovation [36]. Ferreira and Fernandes [14] state that digital strategy formulation and execution reflect a company's openness and progressive culture, and inspire employees to innovate and broaden their thinking. Additionally, Matt and Hess [29] indicate that executing a digital strategy leads companies to prioritise process improvement and innovation of digital and emerging technologies within business processes.

Furthermore, digital strategies allow companies to strengthen their connections with other enterprises, supply chain members, and become more exposed to the market. The data gathered from these connections allows managers to create the foundation for collaborative innovations in supply chain networks [37]. For example, Several Chinese textile companies have successfully adopted digital transformation strategies. For instance, Shenzhou International Group, a leading Chinese textile manufacturer, significantly enhanced its operational efficiency by integrating smart manufacturing processes. Similarly, Youngor Group introduced digital design systems that substantially shortened their production cycles and improved market responsiveness. Lee et al. [38] Highlight how data resources can help enterprises to accurately predict market demand changes, thereby empowering responsive and efficient supply chain collaborative innovations. Similarly, Kwak and Seo [39] state that digital strategies help companies to undertake differentiated product innovations based on market insights.

The nexus between digital transformation and supply chain collaborative innovation can be viewed through the lenses of resource-based view and dynamic capabilities theory. The resource-based view argues that digital transformation equips enterprises with unique capabilities such as data analytics, cloud computing, IoT integration, AI, and others, for reconfiguring the SC resources for innovation [31]. These capabilities allow companies to develop a digital infrastructure that further reduces search coordination costs, and enable firms to externalise R&D costs [2, 40]. On the other hand, the dynamic capabilities theory states that digital tools promote absorptive capacity and thus allow enterprises to assimilate external knowledge [41].

For instance, JD.com's AI-driven inventory system allowed the company to automate supplier communication and helped to cut lead times by 40% [42]. In the textile sector, Jiangsu Sunshine Group, a prominent Chinese textile company, implemented advanced digital analytics and IoT solutions, significantly increasing its collaboration with suppliers and enhancing product innovation. This case exemplifies how digital transformation can actively drive collaborative innovation in China's textile industry. This theory and discussion collectively portray digital transformation as a key solution to establish an open innovation ecosystem. By investing in digital training programs and fostering an innovative culture, firms could be better positioned to leverage digital tools for collaborative R&D. Together, these empirical findings and theoretical frameworks provide a comprehensive understanding of how digital transformation can influence collaborative innovation, and based on this understanding, we can propose this hypothesis:

H1: Digital transformation fosters collaborative innovation in a supply chain network of Textile enterprises.

Supply chain concentration leads the firms to rely on a limited number of suppliers to source the materials/inputs and to sell the final products/outputs to a limited number of customers. This concentration can lead enterprises to leverage digital technologies to foster collaborative innovations. Empirical studies present the dual impact of supply chain concentration to foster or hinder the relationship with key business partners. Tian and Lu [2] show that relying on fewer suppliers/customers can foster collaborative innovations within enterprises as they have balanced integration with flexibility. On the other hand, over-reliance on suppliers/customers can exhibit rigidity as digital investments yield diminishing returns due to limited exposure to diverse ideas and business philosophies [21]. In the case of Huafang Textile Co., Ltd, it is found that a decentralised supplier base allows this company to have enhanced control over the business processes [32]. These findings present an inverted U-shaped nexus, where optimal supply chain concentration promotes integration and flexibility. Firms that maintain a close relationship with a few trusted partners to get routine materials and engage suppliers for specialised materials can achieve stability and innovation. This approach is found to be highly effective in industries where technological uncertainty is high, as firms are required to continuously adapt to emerging trends. Firms with excessive levels of supply chain concentration face challenges in adapting to market shifts because of their reliance on a few dominant partners [9]. Additionally, studies show that moderate supply chain concentration can enable firms to collaborate with startups and research institutions, and thus drive breakthrough innovation in solar and wind technologies [43].

The moderating role of supply chain concentration to influence the nexus of digital transformation with collaborative innovation can be explained through the lens of contingency theory. This theory posits that supply chain concentration has a varying impact, depending on the environmental dynamics. In a stable market environment, high supply chain concentration promotes trust and coordination, thereby amplifying the efficiency gains of digital tools [19]. Firms with concentrated suppliers' networks can benefit from streamlined communications and shared technological standards, thus facilitating the rapid prototyping and co-development of products and services [44]. Conversely, in volatile sectors, low supply chain concentration enables firms to pivot while using digital platforms for engaging with a broader range of partners [45].

Resource dependency theory argues that supply chain concentration determines firms' power of negotiation for data-sharing terms and thus affects innovation equity [46]. For example, Huafu Top Dyed Melange Yarn Co., Ltd., and Jiangsu Sunshine Co., Ltd, have the overall control on their resources to shift toward the radical innovations in their processes. They collaborate with their partner firms to exchange resources and achieve the potential business goals [47]. These theoretical perspectives present the potential role of supply chain concentration to shape digital transformation's outcomes toward innovation. Firms are required to balance the benefits of deep integration with the need for flexibility while adapting to market trends. In highly regulated industries, concentrated supply chains can prioritise compliance over innovation, whereas in tech-driven sectors, decentralised networks can foster agility and creativity. Thus, supply chain concentration can be contingent on both market conditions and industry-specific factors, and thus underscores the importance of strategic partner management to maximise digital transformation benefits. Based on these views, we can propose this hypothesis:

H2: Supply chain concentration influences the nexus between digital transformation and collaborative innovation in the supply chain network of textile enterprises.

METHODOLOGY

Data and sample

The initial sample of this study comprises all A-share textile enterprises of China listed on the Shenzhen and Shanghai Stock Exchanges. The data we collected includes supply chain concentration, financial, and digital transformation of these enterprises for the period of 2011–2022. First, we removed those having spatial or partial treatment in any of the sample years; second, we excluded the firms having missing data for any of the variables for the sample duration; Last, we normalised the sample as per 1% and 99% distribution. The final sample of this study is an unbalanced panel data set of 942 textile firms. The firms studied vary considerably in terms of size, strategies, and digital maturity. Among the sampled companies, approximately 30% are large-sized enterprises with substantial resources dedicated to digital transformation and innovation, around 50% are medium-sized enterprises gradually adopting digital technologies, and roughly 20% are small enterprises at the early stages of digital adoption. Strategies ranged from complete automation and intelligent manufacturing adopted by larger firms to basic digital tools and incremental process enhancements used by smaller companies. The sample is finalised based on the data availability of all variables of the study. While the sampled textile companies share industry-level similarities, variations exist in automation levels, equipment modernity, employee training, and business strategies. Large enterprises typically possess advanced automation systems and extensive training programs, contrasting with smaller firms that rely on manual processes and limited formal training. This heterogeneity is controlled for in our analysis using firm size and growth as control variables. Data on financial, supply chain, and digital transformation is obtained from the China Stock Market and Accounting Research (CSMAR) database. Additional data, such as provincial internet penetration and regional economic growth, is sourced from Chinese Statistical Yearbooks.

Variable selection

Dependent variable: Collaborative Innovation (INOV)

This study uses the natural logarithm of the total number of joint patents obtained by the enterprises within a supply chain network. The calculation is performed by getting the data of joint patents from the CNRDS database. A joint patent is considered a collaborative innovation effort where enterprises engage with their suppliers and customers to promote joint inventions.

Independent variable: Digital transformation

In this study, corporate digital transformation serves as the independent variable, primarily measured by the frequency of digitisation-related terms appearing in the firms' annual reports [48–50]. A similar method is applied by the CSMAR database, and it measures a firm's digital transformation by considering the words relevant to strategic leadership score (SL), technology-driven score (TD), organisational empowerment score (OE), environmental support (ES), digital achievement score (DAC) and digital application score (DAP). This study uses the digital transformation index, provided by CSMAR, for empirical analysis, which is measured as:

$$DigiT_{i,t} = (0.3472 * SL_{i,t}) + (0.162 * TD_{i,t}) + \\ + (0.0969 * OE_{i,t}) + (0.0342 * ES_{i,t}) + \\ + (0.0884 * DAC_{i,t}) + (0.0884 * DAP_{i,t}) \quad (1)$$

where $DigiT_{i,t}$ denotes firm *i*'s digital transformation index in year *t*. $SL_{i,t}$, $TD_{i,t}$, $OE_{i,t}$, $ES_{i,t}$, $DAC_{i,t}$ and $DAP_{i,t}$ represent the firm's strategic leadership score, technology-driven score, organisational empowerment score, environmental support score, digital achievement score, and digital application score, respectively, in year *t*.

Moderating variable: Supply chain concentration

This study uses two primary measures to detect the supply chain concentration's extent [51, 52]. Customer concentration (*CustConc*) is measured as the sum of sales to the five largest customers divided by the total sales of the enterprise *i*. Supplier concentration (*SupConc*) is the sum of purchases from the top five suppliers to the total enterprise's purchases. Therefore, we measure *CustConc* and *SupConc* as follows:

$$CustConc_{i,t} = \left(\frac{sales_{i,j,t}}{sales_{i,t}}\right) \quad (2)$$

$$SupConc_{i,t} = \left(\frac{purchases_{i,j,t}}{purchases_{i,t}}\right) \quad (3)$$

where $sales_{i,j,t}$ denotes the firm *i*'s sales to the top five customers *j* at *t* year, and $sales_{i,t}$ represents the firm *i's* total sales in *t* year. $purchases_{i,j,t}$ denotes firm *i*'s purchases from its top five suppliers *j* at *t* year, and $purchases_{i,t}$ indicates the firm *i*'s total purchases in *t* year. Hence, our study is considering supply chain concentration, so it will comprise both customer concentration (*CustConc*) and supplier concentration (*SupConc*), and take the average of both. So, the formula for supply chain concentration for firm *i* in year *t* will be as follows:

$$SC_{i,t} = (CustConc_{i,t} + SupConc_{i,t})/2 \quad (4)$$

where $SC_{i,t}$ denotes the firm's supply chain concentration of firm *i* in year *t*. Hence, the higher the value of $SC_{i,t}$, *the* higher the supply chain concentration.

Table 1

VARIABLES DEFINITIONS			
Variable type	**Variable name**	**Symbol**	**Variable description**
Explained variable	Collaborative innovation	INOV	The logarithm of the total number of jointly obtained patents.
Independent variable	Firm's digital transformation	DIG	Digital transformation is measured as the digitalisation-related words appearing in annual reports of Chinese manufacturing firms.
Moderator	Supply chain concentration	SCC	Measured as the average of the sum of supplier and customer concentration.
Firm level – Control variables	Firm size	Size	The log of the total assets of the firm.
	Firm growth	Growth	The growth ratio of the total assets of enterprises.
	Financial leverage	FL	The ratio of total liabilities to total assets.
	Firm profitability	-	Return on assets ratio.
	Debt to equity	D/E	Total liabilities to total owners' equity.
Regional level – Control variables	Regional economic development	GDP	The natural logarithm of GDP per capita.
	Financial development level	FIN	The sum of deposits and loans as a proportion of GDP.

Control variables

Following prior work [7, 53], we employ control variables that influence the collaborative innovation of enterprises. In our study, we include the variables of firm size (size), Firm growth (growth), Financial leverage (fl), Firm profitability (profit), Debt to equity ratio (D/E), Regional economic growth (GDP), and Provincial financial development level (fin). The definition for each of the variables of this study is given in table 1.

Econometric modeling

Based on hypothesis 1, we framed this econometric model:

$$CINV_{i,t} = \alpha_0 + \alpha_1 DIG_{i,t} + \alpha_2 X_{i,t} + \varepsilon_{i,t} \tag{7}$$

where $CINV_{i,t}$ is the collaborative innovation level of firm i in year t. $DIG_{i,t}$ reflects the digital transformation level of the firm i in year t. X is the list of control variables, α represents the coefficient value and ε denotes error term.

Further, we examine the Moderating role of supply chain concentration to influence the nexus between digital transformation and collaborative innovation. For state purposes, we introduce SCC in the baseline empirical model and frame the next model. In the next phase, we introduced supply chain concentration (*SCC*) as the Moderating variable to check the Moderating effects of supply chain concentration:

$$SCC_{i,t} = \alpha_0 + \alpha_1 DIG_{i,t} + \alpha_2 X_{i,t} + \varepsilon_{i,t} \tag{8}$$

$$CINV_{i,t} = \alpha_0 + \alpha_1 DIG_{i,t} + \alpha_2 DIG * SCC_{i,t} + \\ + \alpha_3 X_{i,t} + \varepsilon_{i,t} \tag{9}$$

where $SCC_{i,t}$ represents the supply chain concentration of firm i in year t. $SCC_{i,t}$ denotes the Moderating effect of firm *i*'s supply chain concentration on the nexus of digital transformation and collaborative innovation.

RESULTS AND DISCUSSION

Descriptive statistics

Table 2 reports the descriptive statistics for the explanatory, Moderating, and control variables of this study. As shown in table 2, INOV has a mean value

Table 2

DESCRIPTIVE STATISTICS OF VARIABLES					
Variable	**Obs.**	**Mean**	**Std. Dev.**	**Min**	**Max**
INOV	7,416	1.497168	1.46388	0	9
DIG	7,416	37.42654	10.53028	21.2208	79.8123
SCC	7,416	29.26578	15.59583	0	91.27
Size	7,416	22.71735	1.458046	19.2226	28.63649
Growth	7,416	0.1839429	0.2960165	–0.725322	3.757947
FL	7,416	1.305545	0.8619252	–3.29385	8.459463
Profit	7,416	0.0691573	0.0522442	–0.020147	0.721492
D/E	7,416	1.090671	1.365666	0.030342	32.89984
GDP	7,416	11.3084	0.4358811	9.705829	12.15643
FIN	7,416	7.500966	2.408341	0	9.378038

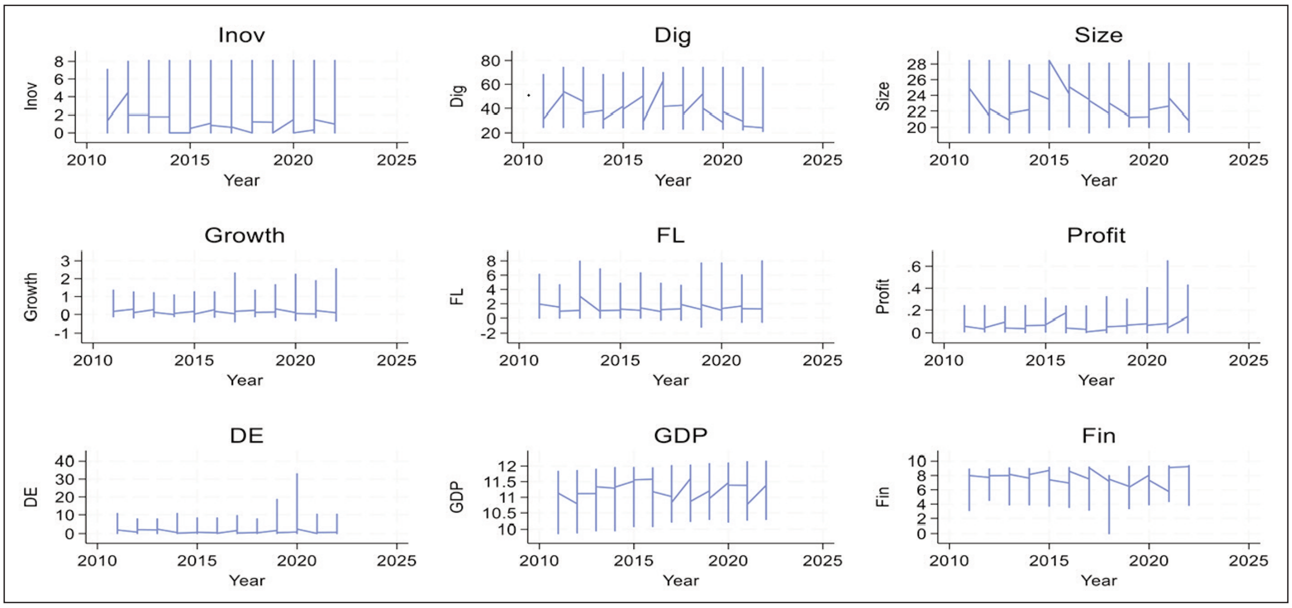

Fig. 1. Variable trends

of 1.4972, indicating the extent to which firms in China have jointly obtained patents or made collaborative innovation efforts. Digital transformation (DIG) has a mean value of 37.4265 with a standard deviation of 10.53028, suggesting that most of the Chinese enterprises are engaged in using digital technologies to gain operational excellence. Supply chain concentration (SCC) reports the mean value of 29.26578, showing the extent to which firms are relying on their major suppliers and customers. Other control variables have shown the normal tendency of the descriptive statistics for the sample period (figure 1).

Pairwise correlation matrix

As per the pairwise correlation matrix results (table 3), DIG shows a positive nexus with INOV, indicated by a correlation coefficient of 0.221. This result implies that an increase in digital transformation of the Chinese listed enterprises results in enhancing the collaborative innovations within supply chain networks. SCC presents a negative coefficient, showing that when firms rely on fewer customers/suppliers, they are likely to compromise on collaborative innovations. They may be influenced by the rigid philosophies and ideas of their partners, and they have to embrace them in their own operations. The nexus between digital transformation (DIG) and supply chain concentration (SCC) is also found to be negative, reflected by a correlation coefficient of –0.114. This indicates that relying on a limited number of customers/suppliers hinders the firms' ability to digitally transform their operations. The correlation values of variables are within an acceptable range and align with prior work [7, 53, 54].

Baseline regression results

The results presented in three columns of table 4 test Hypothesis 1. In column (1), where no fixed effects or control variables are included, the coefficient of DIG is 0.0269, which is highly significant. This suggests a robust positive impact of digital transformation on collaborative innovation within the supply chain network

Table 3

PAIRWISE CORRELATION MATRIX RESULTS

Variable	INOV	DIG	SCC	Size	Growth	FL	Profit	D/E	GDP	FIN
INOV	1.000									
DIG	0.221***	1.000								
SCC	–0.111***	–0.114***	1.000							
Size	0.363***	0.122***	–0.187***	1.000						
Growth	–0.050***	–0.025**	0.082***	–0.117***	1.000					
FL	–0.005	–0.060***	0.005	0.121***	–0.114***	1.000				
Profit	0.016	–0.092***	–0.039***	–0.014	0.187***	–0.213***	1.000			
D/E	0.046***	–0.006	–0.052***	0.341***	–0.076***	0.369***	–0.220***	1.000		
GDP	0.103***	0.130***	0.085***	0.049***	0.034***	–0.141***	0.039***	–0.075	1.000	
FIN	0.039**	0.013	0.008	–0.022*	0.069***	–0.056***	0.008	–0.023**	0.211***	1.000

Note: *, **, and *** indicate the significance level at 10%, 5%, and 1%, respectively.

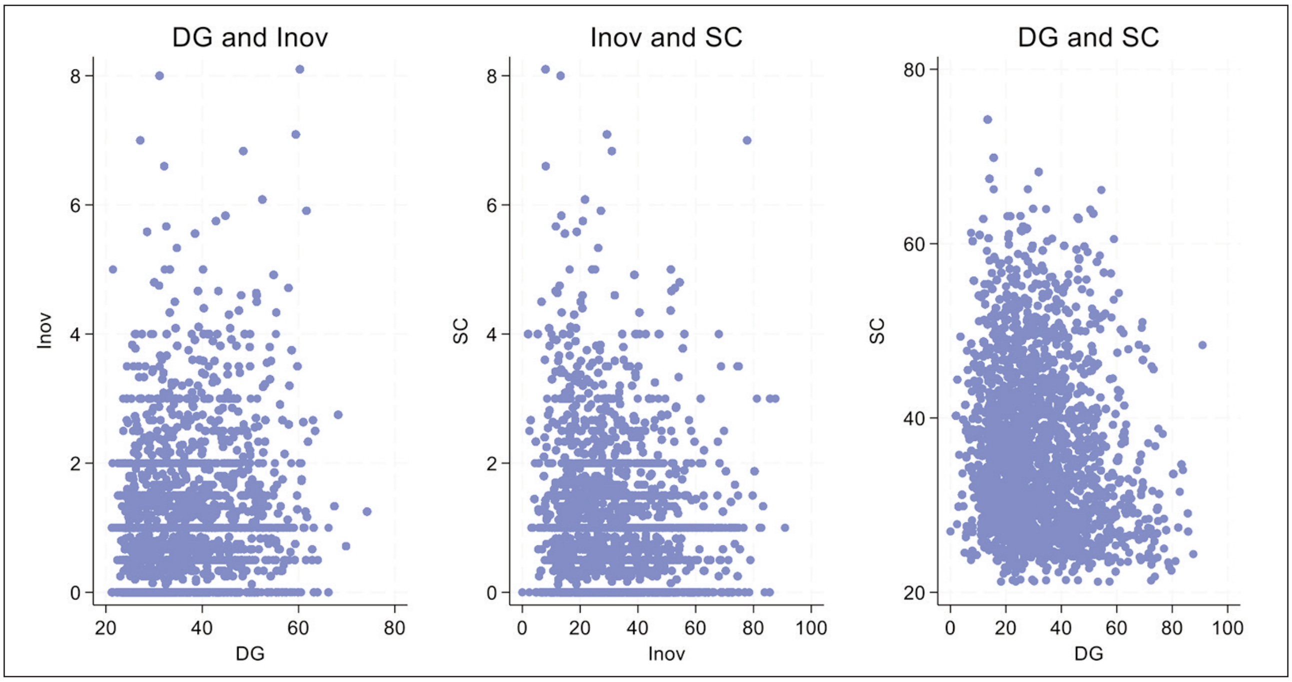

Fig. 2. Nexus between DG, Inov and SCC

Table 4

BASELINE REGRESSION RESULTS			
Variable	**Column (1)**	**Column (2)**	**Column (3)**
	INOV	**INOV**	**INOV**
DIG	0.0269***	0.0149***	0.063**
	(15.23)	(8.39)	(2.23)
SIZE		0.3081***	0.2379***
		(20.71)	(6.61)
GROWTH		–0.0761*	–0.0938**
		(–1.81)	(–1.98)
FL		–0.0018	0.0041
		(–0.11)	(0.23)
PROFIT		–0.0339	–0.3570
		(–0.12)	(–1.07)
D/E		–0.0412***	–0.0314*
		(–3.42)	(–2.07)
GDP		0.3170***	0.6696***
		(7.69)	(8.35)
FIN		0.0184***	0.0187***
		(3.93)	(3.91)
Constant	0.2034***	–9.9429***	–11.7827***
	(2.98)	(–19.93)	(–16.63)
R-squared	0.0486	0.1674	0.1254
N	7,416	7,416	7,416
Firm FE	No	No	Yes
Year FE	No	No	Yes

Note: *, **, and *** indicate the significance level at 10%, 5%, and 1%, respectively. T-statistics are reported in brackets.

of Chinese textile enterprises. This result emphasises the importance of digital transformation in enterprises as they experience an increase in their collaborative innovation efforts when they are more digitally transformed. The column (2), when firm and regional level control variables are included in the model, the coefficient of DIG reduces to 0.0149. Based on this result, we can claim that unobserved firm-level and regional-level variables affect the nexus between digital transformation and collaborative innovation in Chinese textile enterprises. This model further supports the idea that digital transformation is a crucial driver to promote collaborative innovation within the supply chain network of textile companies. The reduction in coefficient suggests that firms with a strong digital transformation strategy possess other capabilities such as leadership, external collaborations, and organisational resources that collectively influence innovation outcomes [55].

In column (3) of table 4, when both firm and year are fixed, and control variables are also included, the coefficient of DIG is reported as 0.063. This increased coefficient in this column suggests that digital transformation, when controlled for temporal and firm-specific factors, has a significant effect on collaborative innovation within the supply chain network of the textile sector of China. This result supports hypothesis 1, claiming the positive impact of digital transformation on collaborative innovation within the supply chain network of Chinese textile enterprises. However, the magnitude of influence is lower than column 1, where no fixed effects and control variables were included, indicating that effects can be moderated by other firm-specific and external factors, such as market conditions, supply chain concentration, or access to digital facilities [56]. This model confirms the direct role of digital transformation in influencing collaborative innovation within the supply chain network, and further argues that there can be other internal or external factors to influence the nexus [57].

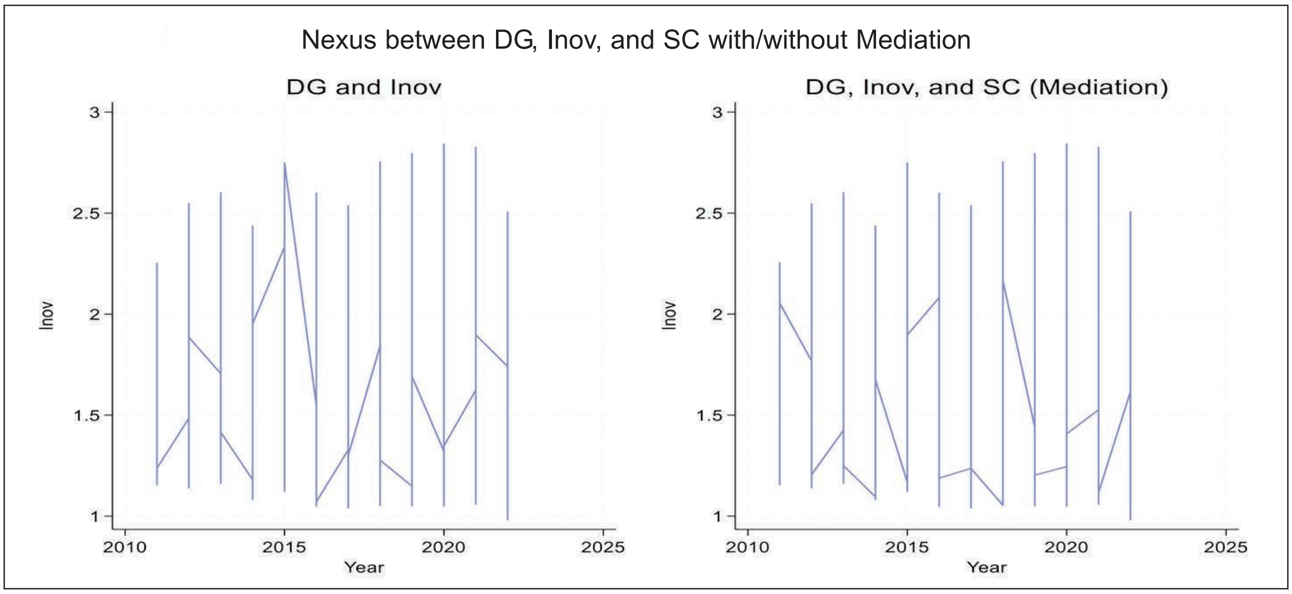

Fig. 3. The baseline and mediation effects

Overall, the baseline results demonstrate that digital transformation has a significant positive impact on collaboration within the supply chain network of Chinese textile enterprises. The findings imply that as firms invest more in digital transformation, they experience a significant increase in their collaborative innovation efforts, which aligns with the growing body of academic literature, demonstrating the role of digital transformation to foster innovations in organisational settings [47, 53, 58]. Digital technologies can be leveraged by enterprises to promote faster decision-making, get access to global knowledge networks, and participate with various partners to gain patents [59]. The positive relationship, presented by the current study, supports the notion that digital transformation enhances a firm's ability to innovate collaboratively, which could be particularly important in industries where innovation is the key to achieving a competitive edge [60]. The varying sizes across the columns suggest that there can be other organisational and environmental factors that may play a significant role in mediating or moderating the nexus between digital transformation and collaborative innovations.

Robustness check using two-stage least squares (2SLS)

To confirm the robustness of baseline results, we employed a two-stage least squares (2SLS) regression approach with an instrumental variable of provincial internet penetration. This variable is widely used in academic literature [54, 61], and this is a valid and effective choice to address endogeneity concerns. Provincial internet penetration could be a strong instrument as it is exogenous to a firm's innovation efforts; however, it shapes the environment for enterprises to adopt digital technologies. The first regression results, reported in column (1) of table 5, present the coefficient of *INTERNET* as 0.1074, which is highly significant. This suggests that increased internet

Table 5

2SLS REGRESSION RESULTS (FIRST AND SECOND STAGE)

Variable	First-Stage	Second Stage
	Column (1)	Column (2)
	DIG	INOV
INTERNET	0.1074***	
	(8.07)	
DIG		0.1007***
		(5.37)
SIZE	0.9204***	0.2868***
	(10.43)	(12.57)
GROWTH	–0.1634	–0.0806
	(–0.39)	(–1.29)
FL	–0.8368***	0.0620**
	(–5.52)	(2.22)
PROFIT	–23.7373***	2.4668***
	(–9.89)	(4.28)
D/E	–0.3512***	–0.0454**
	(–3.49)	(–2.75)
GDP	0.4114	–0.0514
	(1.00)	(–0.75)
FIN	–0.0861*	0.0242***
	(–1.70)	(3.14)
Constant	8.8133*	–8.5746***
	(1.94)	(–14.29)
N	7,416	7,416
F-statistic	F(8,7407) = 54.43	Wald chi2(8) = 993.49
Prob > F	0.0000	0.0000

Note: *, **, and *** indicate the significance level at 10%, 5%, and 1%, respectively. T-statistics are reported in brackets.

penetration across Chinese regions leads to greater digital transformation within firms, which is consistent with the argument that increased internet access fosters digitalisation in a country [62]. Moreover, the f-statistic value of 54.43 considers INTERNET as a strong instrument for DIG. The second-stage regression result, reported in column (2) of table 5, shows the coefficient of 0.1007, demonstrating the positive influence of digital transformation on collaborative innovation within the supply chain network of Chinese listed enterprises. This result confirms the robustness of baseline results that argue the positive impact of digital transformation on collaborative innovation in Chinese textile enterprises.

Mechanism analysis: Moderating effects of supply chain concentration

To further investigate the mechanism through which digital transformation could influence collaborative innovation, we perform moderating effects analysis and report the results in table 6. Supply chain concentration (SCC), relying on fewer customers/suppliers, is employed as the moderating variable to examine its influence on the nexus between digital transformation and collaborative innovation within the textile sector. Column (1) of table 6 presents the direct effects of digital confirmation on collaborative innovation, which are positive, supporting the first hypothesis of the study. Column (2) presents the regression results of model 8, demonstrating the effects of explanatory and control variables on SCC. As per these results, DIG has a regression coefficient of –0.058, indicating that higher digitalisation tends to reduce the supply chain concentration within Chinese textile enterprises. This result implies that when firms are relying on fewer customers/suppliers, the potential to adopt digital technologies may be hindered. In other words, a high level of concentration reduces the number of partners with whom firms may collaborate, and thus limits access to diverse ideas, technologies, and business philosophies [63].

Column (3) shows a negative coefficient of –0.0984 for the interaction term (DIG_SCC), implying that when textile firms are relying on a limited number of suppliers/customers, the effect of digital transformation on collaborative innovation is weakened. This finding argues that while digital transformation serves as the key tool to promote collaborative innovation, its impact gets less pronounced when firms are embedded in concentrated supply chains. This finding supports the idea that competitive dynamics in less concentrated supply chains can spur more innovative behaviour, while concentrated networks can stifle such efforts because of limited external collaboration opportunities [6]. Overall, these results highlight the complexity of the nexus between digital transformation and collaborative innovation in the Chinese textile sector. The moderating effects analysis shows that the benefits of digital technologies to foster innovation could be based on the structure of supply chains. Textile firms in less concentrated supply chains may gain strong innovative benefits from digitalisation, as they have the diversification in their partnerships across various suppliers and customers, which influences their ability to innovate [64].

Table 6

MODERATING EFFECTS OF SUPPLY CHAIN CONCENTRATION (SCC)

Variable	Column (1)	Column (2)	Column (3)
	INOV	SCC	INOV
DIG	0.0633**	–0.058**	0.0087*
	(2.23)	(–2.26)	(1.90)
SIZE	0.2379***	–1.7773***	0.2333***
	(6.61)	(–6.15)	(6.47)
GROWTH	–0.0938*	1.9494***	–0.0864*
	(–1.98)	(5.14)	(–1.82)
FL	0.0041	–0.1414	0.0033
	(0.23)	(–0.98)	(0.18)
PROFIT	–0.3570	4.9452*	–0.3372
	(–1.07)	(1.85)	(–1.01)
D/E	–0.0314**	0.4517***	–0.0296**
	(–2.07)	(3.72)	(–1.95)
GDP	0.6696***	8.6590***	0.6967***
	(8.35)	(13.45)	(8.60)
FIN	0.0187***	–0.0788**	0.0185***
	(3.91)	(–2.05)	(3.86)
DIG_SCC			–0.0984**
			(–2.27)
Constant	–11.7827***	–28.4780***	–11.9728***
	(–16.63)	(–5.01)	(–16.79)
R-squared	0.0879	0.0440	0.0887
N	7,416	7,416	7,416
Firm FE and Year FE	Yes	Yes	Yes

Note: *, **, and *** indicate the significance level at 10%, 5%, and 1%, respectively. T-statistics are reported in brackets.

Additionally, geographic clustering significantly impacts firms' innovation capabilities. Companies located in industrially advanced regions like Zhejiang and Jiangsu exhibit better digital infrastructure, facilitating innovation-driven collaborations. Conversely, companies in less-developed inland regions face infrastructural constraints hindering their collaborative innovation efforts. Policies that enhance digital infrastructure and encourage regional collaboration could bridge this gap, improving overall industry performance.

Heterogeneity analysis

We further perform heterogeneity analysis to show how varying pollution levels of enterprises and firm sizes could influence the nexus between digital transformation and collaborative innovation in the textile sector. Previous studies show that environmental challenges, such as high pollution levels, could necessitate the demand for more partnerships for innovations [65], as firms may leverage digital advancements to comply with strict regulations. As shown in table 7, DIG has a statistically significant value of 0.078 for only heavily polluted industries' enterprises. This finding supports the idea that in

Table 7

FIRM LEVEL HETEROGENEITY – HEAVILY POLLUTED OR NOT		
Variable	**Column (1)**	**Column (2)**
	Heavily polluted	**Non-Heavily polluted**
	INOV	**INOV**
DIG	0.078**	0.056
	(1.97)	(1.37)
SIZE	0.2524***	0.2546***
	(4.64)	(4.83)
GROWTH	–0.1084*	–0.1145
	(–1.75)	(–1.53)
FL	0.0009	–0.0055
	(0.03)	(–0.22)
PROFIT	–0.0758	–0.8458
	(–0.18)	(–1.60)
D/E	–0.0271	–0.0344*
	(–0.94)	(–1.86)
GDP	0.6385***	0.6660***
	(5.00)	(6.08)
FIN	0.0208***	0.0169**
	(3.01)	(2.57)
Constant	–11.8801***	–12.0099***
	(–11.58)	(–11.74)
R-squared	0.0946	0.0838
N	3,311	4,105

Note: *, **, and *** indicate the significance level at 10%, 5%, and 1%, respectively. T-statistics are reported in brackets.

Table 8

FIRM LEVEL HETEROGENEITY – SMALL SIZE VS LARGE SIZE		
Variable	**Column (1)**	**Column (2)**
	Small Size	**Large Size**
	INOV	**INOV**
DIG	0.0121***	–0.0097
	(2.95)	(–0.23)
SIZE	0.2631***	0.2698***
	(4.16)	(4.14)
GROWTH	0.0367	–0.1460***
	(0.36)	(–2.67)
FL	–0.0127	0.0106
	(–0.53)	(0.37)
PROFIT	–1.3934**	0.6699
	(–2.66)	(1.41)
D/E	–0.0317	–0.0211
	(–1.59)	(–0.86)
GDP	0.7827***	0.3751***
	(6.65)	(2.98)
FIN	0.0218***	0.0071
	(3.18)	(1.10)
Constant	–13.7071***	–8.9899***
	(–11.52)	(–7.27)
R-squared	0.1065	0.0372
N	3,691	3,725

Note: *, **, and *** indicate the significance level at 10%, 5%, and 1%, respectively. T-statistics are reported in brackets.

industries where pollution is a major concern, firms use more digital technologies to promote collaborative innovations [66]. Moreover, we can see that GDP and FIN have positive effects on INOV, indicating the role of economic growth and financial performance in promoting collaborative innovations [67]. Overall, these findings highlight the environmental challenges and firm characteristics to frame the effects of digital transformation on collaborative innovations.

Firm size could be another factor influencing the ability of enterprises to adopt and benefit from digital technologies [68]. Previous studies show that large-sized firms typically have more resources, better infrastructure, and better capabilities to deploy digital solutions and innovate more [69]. Firm-size heterogeneity analysis results are shown in table 8, showing the greater and significant effects of digitalisation for small-sized firms. This finding suggests that small-sized firms have fewer resources and they have to rely more on digital transformation for growth and innovation, so they deploy more technologies in their processes [70]. The large-sized firms may have bureaucratic and rigid structures, so they may not effectively employ digital technologies to foster collaborative innovations. Overall, the findings of the current study highlight how firm size could moderate the role of digital transformation to drive innovation, with smaller-sized firms showing greater reliance on digitalisation.

CONCLUSION AND POLICY IMPLICATIONS

Textile firms, relying on fewer customers and suppliers, could be exposed to opportunities and challenges. This concentration can influence their digital strategies, employed to achieve collaborative innovations, and may promote or hinder them. Based on this idea, this study primarily examines the nexus between digital transformation and collaborative innovation. Secondly, it analyses the moderating effects of supply chain concentration on the nexus between digital transformation and supply chain concentration. Using the data of 942 Chinese A-share listed textile firms from 2011 to 2022, this study shows that digital transformation has a significant positive impact on collaborative innovation within firms' supply chain networks. Robustness check also supports the benchmark results of the positive impact of digital transformation on collaborative innovations within Chinese textile enterprises. However, moderating effects analysis shows that relying on limited suppliers/customers hinders the ability of firms to fully leverage the benefits of digitalisation for fostering collaborative innovations. Furthermore, industry pollution level and firm size are found to be significant factors influencing the firms' ability to leverage digital technologies to foster collaborative innovation. Our findings highlight specific companies like Shenzhou International and Jiangsu Sunshine Group as successful exemplars leveraging digital transformation for collaborative innovation. To assist firms struggling with digital transformation, we recommend targeted solutions, including increased government support for digital literacy programs, incentives for digital infrastructure investments, and strategies encouraging diversified partnerships within supply chains. Other textile firms (those that don't employ digital technologies in their processes today) could follow these companies to enhance their strategic capability to partner with other firms and achieve their potential goals. It could be critically important for those firms to understand their digitalisation requirements to bring strategic collaborations in different areas.

There are several policy implications presented by the findings of this study. First, from a government perspective, policymakers should promote policies that can promote digital infrastructure, as expanding digitalisation across all regions, improving financial inclusion, and offering benefits to enterprises, allowing them to own efficient resources. Second, policymakers of Chinese textile enterprises should set those innovation targets for enterprises that can be achieved through cooperation, so they can be ready to participate with each other. Third, from a firm perspective, managers in Chinese textile enterprises should diversify their customer base and supplier base to have more partners in a position to achieve the benefits of digitalisation for collaborative innovations. They should promote the development of competitive and diverse supply chains so that there can be collaborations across various enterprises. Fourth, Chinese textile firms should not only leverage digital technologies for operational efficiency, but they should also use them to ensure environmental sustainability. Last, textile companies can practically apply the study's insights through actions such as: (1) Investing in modular digital platforms that enhance supplier interaction and flexibility, (2) Establishing joint digital training initiatives with suppliers and customers to improve collective digital capabilities, and (3) Diversifying their supplier/customer bases to leverage broader innovation networks, thus reducing the risks associated with high supply chain concentration.

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Body shape morphology representation and prototype pattern optimisation by polar diameter on female students' "waist-to-thigh" zone

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ABSTRACT – REZUMAT

Body shape morphology representation and prototype pattern optimisation by polar diameter on female students' "waist-to-thigh" zone

Traditional prototype patterns are typically generated using proportional formulas based on size specifications. This will only receive identical prototype patterns under the same size specification, directly leading to significant fit issues due to morphology differences. A 3D point cloud of 353 female students was scanned, and the cross-section layers of the 'waist-to-thigh' zone were determined. A polar radial was extracted to represent the surface morphological difference. Subsequently, the pattern based on the surface flattening was optimised. Additionally, the fitness was evaluated by the subjective assessment. The results showed that the polar radial could represent the body morphological difference even under the same size specification. Based on the morphological difference, the 160/68A could be divided into three categories: 160/68A-Type-I, Uniform (46.79%), 160/68A-Type-II, Flat subelliptic (37.01%) and 160/68A-Type-III, Convex subcircular (16.2%). The corresponding optimised pattern could effectively improve the garment's fitness by integrating the body morphology while maintaining original size specifications. Particularly in the waist and side seam region, the dressing pressure had been effectively solved because the pattern is more in line with the shape morphology characteristics. These findings will contribute to the fitness improvement of the same size specification.

Keywords: *body morphology, pattern generation, surface flattening, garment fitness, pattern optimisation*

Reprezentarea morfologică a formei corpului studentelor și optimizarea prototiparelor pe baza diametrului polar în zona "talie-șolduri"

Prototiparele tradiționale sunt generate, de obicei, folosind formule proporționale bazate pe specificații de mărime. Această abordare generează prototipare identice doar pentru aceeași specificație de mărime, ceea ce duce direct la probleme semnificative de potrivire din cauza diferențelor morfologice. A fost scanat un nor de puncte 3D al unui număr de 353 de studente și au fost determinate straturile secțiunii transversale din zona "talie-șolduri". S-a extras un parametru radial în coordonate polare pentru a reprezenta diferența morfologică a suprafeței. Ulterior, modelul bazat pe aplatizarea suprafeței a fost optimizat. În plus, potrivirea a fost evaluată prin evaluare subiectivă. Rezultatele au arătat că parametrul radial în coordonate polare poate reprezenta diferența morfologică a corpului chiar și în cazul aceleiași specificații de mărime. Pe baza diferenței morfologice, 160/68A a putut fi împărțit în trei categorii: 160/68A-Tipul I, Uniform (46,79%), 160/68A-Tipul II, subeliptic plat (37,01%) și 160/68A-Tipul III, subcircular convex (16,2%). Modelul optimizat corespunzător ar putea îmbunătăți în mod eficient potrivirea articolului vestimentar datorită integrării morfologiei corpului, menținând în același timp specificațiile originale de mărime. În special în zona taliei și a cusăturii laterale, presiunea exercitată de îmbrăcăminte a fost rezolvată în mod eficient, deoarece modelul este mai în concordanță cu caracteristicile morfologice ale formei corpului. Aceste constatări vor contribui la îmbunătățirea potrivirii pentru aceeași specificație de mărime.

Cuvinte-cheie*: morfologia corpului, generarea tiparelor, aplatizarea suprafeței, potrivirea articolelor vestimentare; optimizarea tiparelor*

INTRODUCTION

Statistics indicated that 67% consumers prioritise garment fitness over factors such as style, colour, and price [1]. This underscores the garment's fitness as a crucial determinant of both quality and consumer satisfaction, making it a core aspect of garment ergonomics [2, 3].

A well-fitting pattern is essential for achieving garment fitness [4]. Among various pattern-making methods, the prototype pattern method is the most widely used in industrial production due to its balance between industrialisation and personalisation. However, prototype methods, such as the Japanese Bunka, Dressmaker, and Donghua prototypes, rely on proportional formulas based on size specifications [5]. However, individuals under the same size specification may have different body morphologies [6]. Size-based prototype patterns fail to effectively capture morphological variations in contour, posture, and proportion, leading to noticeable fitness issues under the same size specification [7]. Thus, it is crucial to

incorporate body morphological information into the prototype pattern generation. It will be an important means of solving these garment-fitting problems.
To optimise pattern generation based on morphological differences, researchers have explored several approaches. One method involves optimising prototype patterns by incorporating morphological parameters beyond basic body measurements, such as chest girth, waist girth, hip girth, shoulder width, etc. [8, 9]. Additionally, more detailed morphological parameters, like shoulder sloping, volume of abdomen, posture, etc., are also involved in refining the garment's fitness [10]. While these approaches improve garment fit, they also increase the complexity and slow down the pattern generation process [7]. To address this, virtual try-on technology provides an alternative by enabling real-time pattern adjustments in a digital environment [11]. This allows continuous adjustments without the physical garments. For this purpose, Sohn et al. [12] developed the virtual try-on framework to adjust the pattern to improve fitness. Ding et al. [4] designed and optimised the men's garment block pattern in CLO 3D. And the dressing pressure and actual wearing were used to reflect the garment's fitness. Meanwhile, the collaborative learning in the practice teaching of garment 3D virtual fitting to co-design and make their own garments was proposed [13, 14]. Recently, AI-integrated virtual technologies have also emerged [15]. The fitness could be further enhanced by leveraging machine learning or deep learning to analyse body shape variations and predict optimal garment adjustments. However, these applications are mainly aimed at garment design, with manual adjustments making the process time-consuming.
Another approach focuses on optimising patterns based on the human body subdivision. Lei [16] analysed the limitations of the prototype pattern, particularly in the representation of complex body shapes. Furthermore, the human body subdivision was proposed to enhance the matching degree between pattern and body morphology [17, 18]. Meanwhile, this method has been demonstrated to be effective in reducing fitness problems, especially in irregular or asymmetrical morphological [19]. Pandarum et al. [20] utilised a new normative method based on the scanning data to subdivide the human body into nine morphotype categories, acquiring the morphological features. Similarly, Gu et al. [17] combined the k-means cluster and discriminant rules to classify the human body into four categories. Subsequently, the surface flattening was used to obtain the corresponding subdivision patterns. We also proposed the space vector index to represent and quantify the body surface morphology; the corresponding patterns were also obtained [21]. However, these methods fail to capture the morphological difference under the same size specification, directly limiting improvements in garment fitness. To bridge this gap, morphological variations are first systematically analysed. Then, these variations are integrated into prototype pattern generation to enhance fitness while maintaining original size specifications.
In this study, the integration of morphological differences under the same size specification was proposed. Trousers were chosen as the experimental samples, focusing on the waist-abdomen-hip zone due to its complex morphology. Polar radials were extracted from the cross-section layers for precise morphological characterisation. PCA and K-means clustering were employed to classify target zones, followed by surface flattening to optimise corresponding patterns. Finally, virtual fitting evaluations were conducted to assess improvements. The findings enhance garment fitness by systematically incorporating morphological differences into prototype pattern generation. It not only enhances garment fitness but also provides a reference for mass customisation in the apparel industry by integrating morphological analysis techniques.

EXPERIMENT SECTION

Anthropometric

A total of 353 female university students, aged from 18 to 25 years, were recruited for this experiment, exceeding the minimum required sample size of 282 as determined by the minimum sample size based on the Chinese national standard GB/T 22187-2008. After outlier testing and descriptive analysis, 307 valid samples were determined, meeting the experimental sample requirements. Then, to obtain 3D cloud data, the $[TC]^2$ body scanner (NX-16, America) was utilised. Following ISO 20685-1:2018(E), the scanning garment should be minimal, with the subjects' acceptance, considering the cultural differences. And the mean value of three-time-repeated scanning to reduce systematic error. The experiment was conducted in a controlled environment with the temperature of (27±3) ºC and the relative humidity of (60±5)%.

Basic cross-section extraction

Based on the relationship between the lower body morphology and trousers' structure, which could be divided into four areas: fitness, activity, free and design area. The "waist-to-thigh" zone is the primary factor influencing trousers' fitness, while the zone below the thigh root is designated as the design area. Thus, the 'waist-to-thigh' zone was selected as the target zone (figure 1). Considering the correspondence between the lower body morphology and the trousers' structural lines, the waist, abdomen, hip and thigh were selected as the basic cross-sections for analysis.
The point-cloud data derived by 3D scanning was imported into reverse engineering (*Imageware 13.2*) to reconstruct the human body with unrelated parts removed. The Parallel Point Cloud Section was applied to extract the basic cross-sections, following the approach outlined in [21]. Cross-sections extracted from scanned data often contain noise and errors due to equipment limitations, tester variability, and

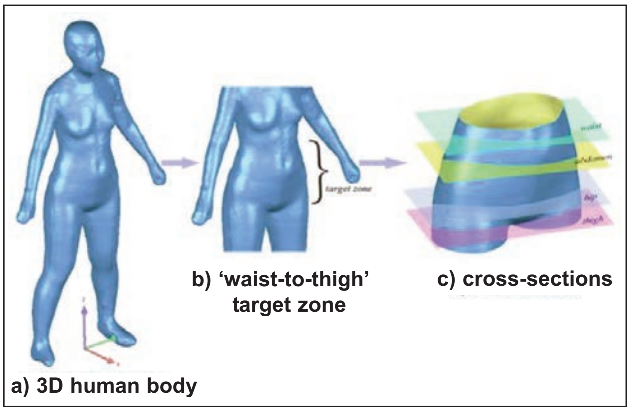

Fig. 1. Determination of basic cross-section

others. To address these, mending, smoothing, and straightening processes were applied to obtain continuous and smooth point-cloud data using MATLAB 2017a (Math Works, Inc.) The producers were referred to Zhang's study [22].

Polar radial extraction

Curve fitting

To generate cross-section curves that align with morphological characteristics, the processed point-cloud data required further curve fitting. Considering the sparse distribution, high iteration, and nonlinear nature of the cloud data, the cerebellar model articulation controller (CMAC) neural network was employed to fit the cloud data into the cross-section curve. Unlike conventional neural networks, the CMAC is a local approximation model that eliminates the need for predefined network depth and neuron numbers. These features endow the CMAC with significant advantages in convergence speed, local generalisation capability, and fitting accuracy. Taking the waist cross-section as an example, the fitting results were illustrated in figure 2, *a* and *b*. It demonstrates that the model achieves the desired fitting accuracy through parameter tuning.

Polar radial extraction

Based on the sampling points along the cross-sectional curve, an orthogonal coordinate system was constructed. This system utilises radial lengths at various positions to characterise the morphological variations. The X-axis aligns with the sagittal plane and the Y-axis with the coronal plane. And the intersection was the centre point. Sampling points were marked every 10º along the cross-section curve, and the horizontal vector was used to define the polar length. Then, a total of 37 feature points were extracted. Figure 2, *c* illustrates the distribution of these 37 points and the polar radial. The corresponding polar radial lengths at different positions were illustrated in figure 2, *d*. To clearly illustrate the radial differences at different positions, the extracted samsampling points were divided into four regions: Back-Middle ($No._{i1}$ to $No._{i7}$ and $No._{i31}$ to $No._{i1}$, purple), Left-Side ($No._{i1}$ to $No._{i7}$ and $No._{i31}$ to $No._{i1}$, green), Right-Side ($No._{i1}$ to $No._{i7}$ and $No._{i31}$ to $No._{i1}$, pink) and Front-middle ($No._{i13}$ to $No._{i25}$, yellow).

RESULTS AND DISCUSSION

Determination of the target size specification

The process of determining the target size specification was mainly divided into three steps.

(1) Height selection: The 160 category is the highest proportion under the national standard (GB/T 1335.2-2008), accounting for 37.79%.

(2) Specification within height group: By combining the height category with type A, the 160-A was formed.

(3) Circumference selection: Within the 160-A framework, the 160/68 A size specification has the highest proportion, reaching 43.06%. Then, the final target size specification (160/68 A) was determined. It also aligns with the distribution phenomenon defined by the national standard. Additionally, normality testing was conducted to reveal that both height and size type generally followed the normal distribution. Based on the distribution results, the 31 corresponding samples under the 160/68 A occupied the largest proportion. Thus, these 31 samples were selected as the target size specification.

Human body subdivision (160/68 A)

PCA and K-means cluster analysis

After determining the target size specification, the polar radial reached 4588-dimensional (31×4×37), directly affect the algorithm accuracy and speed. To address this, Principal Component Analysis (PCA) was employed to reduce dimensionality while retaining essential information. Through the PCA of the

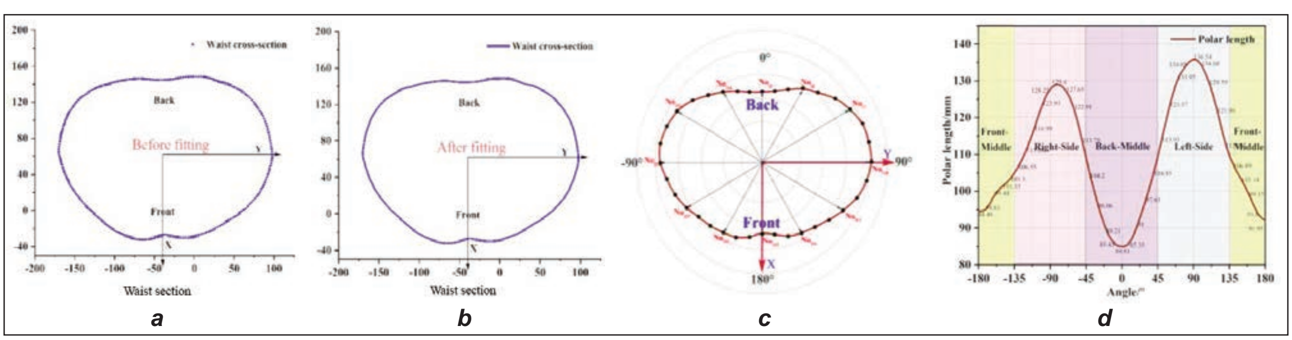

Fig. 2. Polar radial extraction: *a* – before fitting; *b* – after fitting; *c* – points distribution; *d* – polar lengths

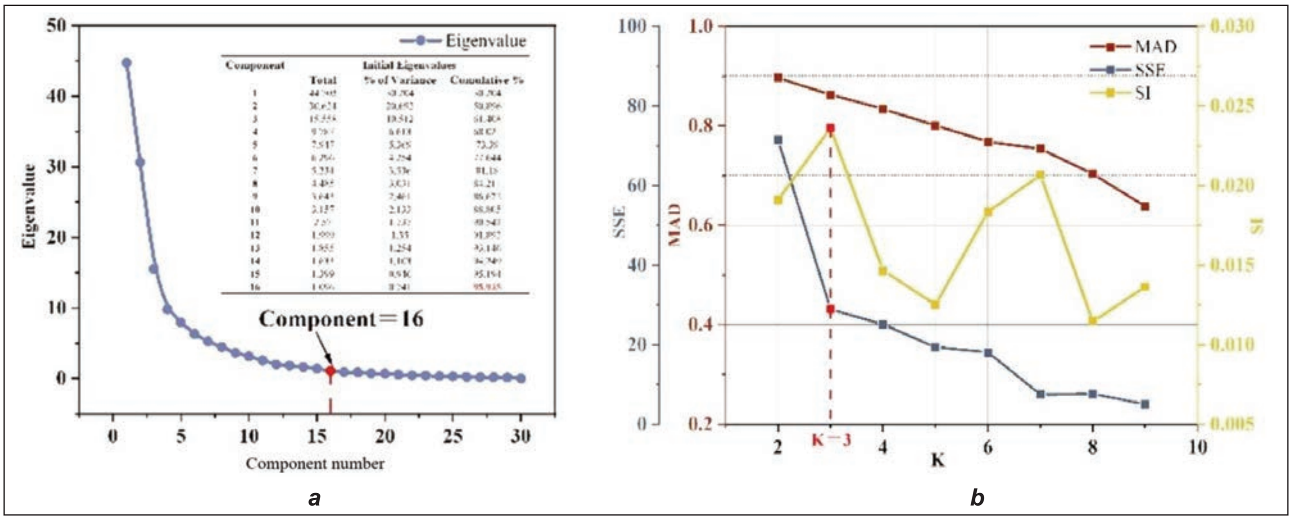

Fig. 3. PCA and K-means cluster analysis: *a* – PCA analysis; *b* – evaluation of cluster number *k*

‘princomp’ function in Matlab, PCA yielded a cumulative contribution rate of ρ = 95.762% was obtained (figure 3, *a*). It indicated that 16 principal components could sufficiently describe the morphological characteristics of the target zone.

Next, the K-means was applied for human shape subdivision. However, the choice of cluster number *k* significantly affects the algorithm’s performance. To determine the optimal *k*, three evaluation metrics were employed: mean absolute deviation (MAD), the sum of squares due to error (SSE) and silhouette index (SI). As shown in figure 3, *b*, the MAD showed a downward trend with minimal slope variation, indicating no abrupt changes. The SSE decreased sharply at 3, forming an elbow point, suggesting that $k = 3$ is the optimal cluster number. Simultaneously, the SI reached its peak at $k = 3$, also supporting this choice. Thus, the final *k* was determined to be 3.

Human body subdivision

After determining the number of clusters as 3, the human body subdivision was realised using K-means. The 160/68A was further subdivided into three categories: Type-I (46.79%) > Type-II (37.01%) > Type-III (16.2%). And the three subdivision results of the intermediate shape are shown in figure 4. It could be seen that the morphological differences among them were evident. This finding highlights that individuals with the same size data can exhibit distinct body shapes, which is a key factor contributing to garment unfitness.

The morphological differences were illustrated: Type-I (Uniform): the overall shape is moderately cocked, with a balanced contour and an appropriate waist-to-hip thickness. Type-II (Flat subelliptic): the overall body shape is relatively flat, with a wider waist, abdomen, and hip, but smaller waist-to-hip thickness. Type-III (Convex subcircular): the overall shape is rounded, with a prominent waist, abdomen and hip, resulting in a larger waist-to-hip thickness.

Shape morphology representation

To highlight the morphological differences among the 3 subdivision types, figure 5, *a* illustrated the overlapped results of the same cross-sections, while figure 5, *b* shows the difference in the polar radial. Among them, Type-I was used as the reference. As we can see, in the waist cross-section, Type-II exhibits a larger polar length than Type-I on the right and left sides, but a smaller one in the front and back-middle. In contrast, Type-III demonstrates the opposite phenomenon relative to Type-II. A similar trend is observed in the abdomen. Although the differences are more pronounced, with a maximum deviation of 1.84 cm. In the hip, Type-II shows a larger polar length, primarily on the right side, and a smaller one in the front-middle. Conversely, Type-III exhibits larger values than Type-I in the front and back-middle areas, while being smaller in the lateral middle, with a maximum difference of 0.90 cm. In the thigh root, the morphological differences show a similar phenomenon between Type-II and Type-III. They are all larger than Type-I in the front and back-middle positions, but smaller in the lateral middle regions. Overall, the shape morphology of Type-II is relatively flat, while that of Type-III is a convex subcircular.

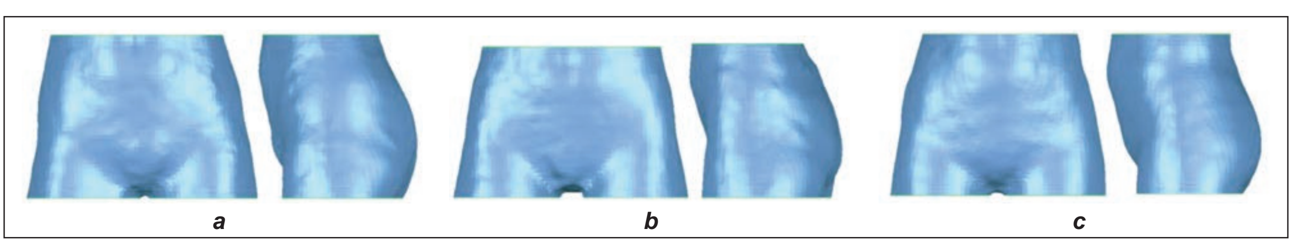

Fig. 4. Human body subdivision: *a* – 160/68A-Type-I; *b* – 160/68A-Type-II; *c* – 160/68A-Type-III

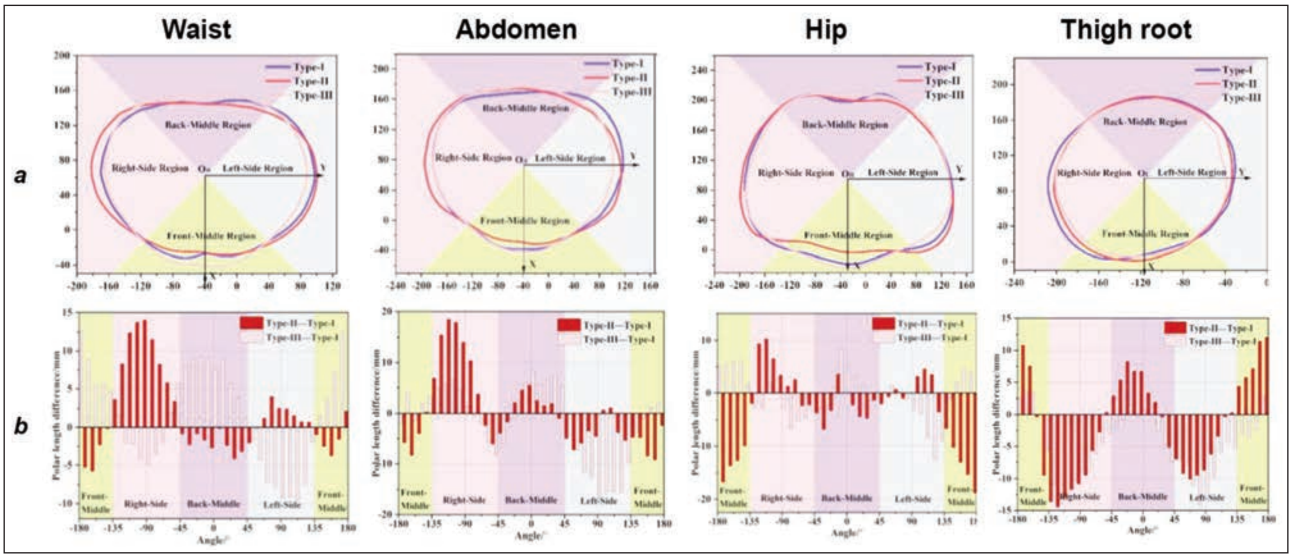

Fig. 5. Shape morphology representation and comparison

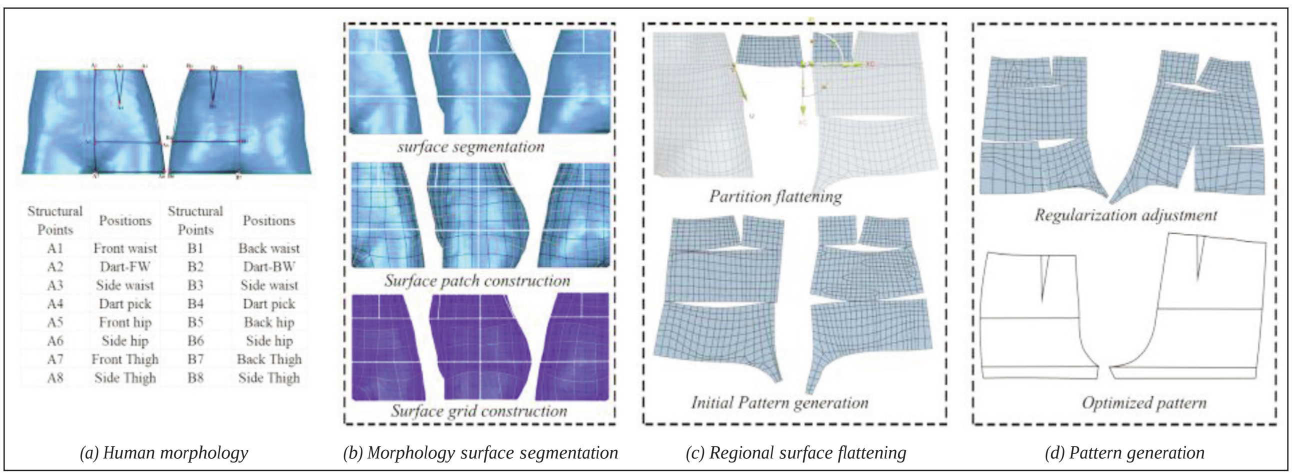

Fig. 6. Optimised pattern based on surface flattening

Prototype pattern optimization

Pattern optimisation based on surface flattening

To obtain the pattern incorporating morphological characteristics, the surface flattening method was applied. This approach not only enables the transformation of 3D surface geometry into 2D planar patterns but also allows the integration of local curvature and deformation constraints, ensuring that the resulting flat patterns maintain fidelity to the original 3D form. According to the structure characteristic of the trousers' prototype pattern, the 16 structure points corresponding to the target zone were selected. Then these points were divided into several regions (figure 6, *a*). Then, the morphological surface was segmented by constructing patches and grids on the 3D body surface model, generating the fitted surface (figure 6, *b*). For each segment part of the morphological surface, surface flattening was performed on the fitted surface to generate an initial pattern (figure 6, *c*). Since the surface morphology is 3D, the initial flattened surface pattern has a certain degree of inclination and curvature. The regularisation adjustments were applied to the structural lines based on the prototype patternmaking rules. As a result, the optimised pattern was acquired in figure 6, *d*.

Figure 7 illustrates the three subdivision patterns and pattern prototypes under the 160/68A size specification. As we can see, although the obvious waist circumference and length are the same, the local details show differences. Compared with the pattern prototype, different subdivision types, dart sizes, and locations of the front/back pattern pieces are also

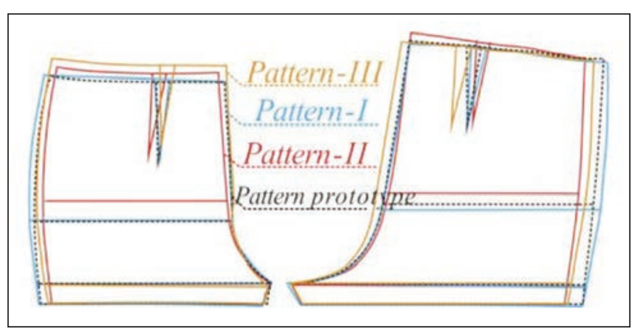

Fig. 7. Comparison of different subdivision patterns

Table 1

DETAILED DATA OF THE HUMAN BODY					
Height (cm)	**Weight (kg)**	**Waist circumference (cm)**	**Hip circumference (cm)**	**Thigh circumference (cm)**	**Subdivision category**
161.4	48	67.6	87.4	52.5	Type-II

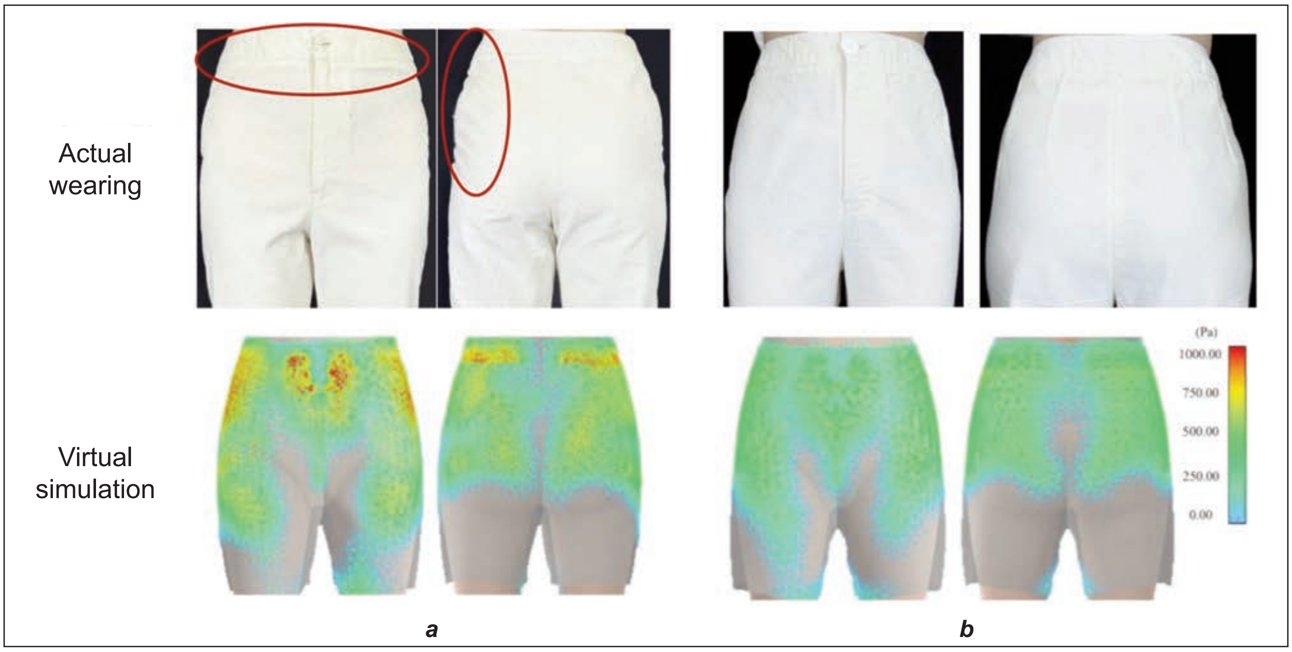

Fig. 8. Results of fitness comparison: *a* – pattern prototype; *b* – pattern-II Flat subelliptic

different. Among them, the waist width becomes Pattern-III> Pattern-I> Pattern-II, the same as the back waist dart location. Furthermore, the difference between the waist-abdomen is Pattern-I> Pattern-II> Pattern-III. This also basically conforms to the morphological representation illustrated in the previous section.

Fitness comparison

To demonstrate the fitness improvement of the proposed method, both actual wear trials and virtual simulations were conducted. Among them, the target subject was recruited, and the detailed data are presented in tabel 1. According to the subdivision results, the subject belongs to the Type-II category. Then, the materials used in actual were the 2222 plain fabric. And the actual garment was made by the tailor patternmakers based on the pattern prototype and subdivision pattern. For the virtual simulation, the detailed data of the target subject was imported into the Style 3D to generate the virtual model. The pattern prototype and subdivision pattern were then virtually sewn to make a comparison. The built-in strain map module was utilised to visualise. Figure 8 illustrates the results of the fitness comparison. As we can see, there is almost the same in the silhouette of the trousers. However, the prototype pattern produced more pronounced wrinkling and drag around the waist and side seams, indicated by yellow and red regions in the simulation. In contrast, the subdivision pattern-II conformed more closely to the body morphology characteristics, indicating blue and green in virtual simulation. These results will contribute to the fitness improvement of the trousers.

CONCLUSION

In this study, the integration of morphological differences under the same size specification was proposed to enhance pattern prototype fitness. The main conclusions were drawn as follows:

(1) Experiments showed that the polar radial could represent the body morphological difference under the same size specification. Based on the morphological difference, the “waist-abdomen-hip” zone was classified into three categories: Type-I (41.79%) > Type-II (28.79%) > Type-III (16.1%).

(2) The optimised prototype pattern could effectively improve the fitness while maintaining the original size specifications. Particularly in the waist and side seam region, the dressing pressure had been effectively solved because the pattern is more in line with the shape morphology characteristics.

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A literature review of textile industry carbon emissions research: research hotspots, themes and emerging trends

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XU CHEN
XUFENG WU
PEIHUA HAN
DI WU

ABSTRACT – REZUMAT

A literature review of textile industry carbon emissions research: research hotspots, themes and emerging trends

As global climate change issues became increasingly severe, the textile industry, characterised as a high-energy consumption and high-emission sector, attracted widespread attention regarding its carbon emission challenges. Exploring the current status of textile industry carbon emissions and identifying emission-reduction pathways has emerged as a prominent focus in environmental science research. To understand the research status of textile industry carbon emissions and clarify the research trajectories and future directions of textile carbon reduction, this study employed bibliometric methods, utilising literature on textile industry carbon emissions from the Web of Science database (2005–2025) as the analytical subject. CiteSpace visualisation software was used to analyse the research domains and core content of textile industry carbon emissions over 20 years. Through examining citation frequencies, the study assessed research hotspots in textile industry carbon emissions and predicted development trends in textile carbon reduction research. The research findings indicated that since 2012, the volume of research on textile industry carbon emissions has demonstrated exponential growth. Research outcomes were predominantly published in environmental science and sustainability journals, whilst traditional textile journals exhibited lower publication volumes, suggesting that interdisciplinary and multidisciplinary research in textile industry carbon emissions remained relatively weak, with research quality requiring improvement. The development of clean production technologies and circular economy models influenced and promoted the green transformation of the textile industry, leading the direction towards a low-carbon textile era.

Keywords: *textile industry, carbon emissions, carbon footprint, visualisation analysis, low-carbon textile era*

O analiză a literaturii de specialitate privind cercetarea emisiilor de carbon din industria textilă: domenii de interes, teme și tendințe emergente

Pe măsură ce problemele legate de schimbările climatice la nivel global au devenit din ce în ce mai grave, industria textilă, caracterizată ca fiind un sector cu consum energetic ridicat și emisii semnificative, a atras o atenție sporită în ceea ce privește provocările legate de emisiile de carbon. Analizarea situației actuale a emisiilor de carbon din industria textilă și identificarea căilor de reducere a emisiilor au devenit un punct central al cercetării în domeniul științelor mediului. Pentru a înțelege stadiul cercetării privind emisiile de carbon din industria textilă și pentru a clarifica traiectoriile de cercetare și direcțiile viitoare ale reducerii emisiilor de carbon din industria textilă, acest studiu a utilizat metode bibliometrice, folosind literatura de specialitate privind emisiile de carbon din industria textilă din baza de date Web of Science (2005–2025) ca subiect de analiză. Software-ul de vizualizare CiteSpace a fost utilizat pentru a analiza domeniile de cercetare și conținutul principal al emisiilor de carbon din industria textilă pe o perioadă de 20 de ani. Prin examinarea numărului de citări, studiul a evaluat punctele de interes ale cercetării privind emisiile de carbon din industria textilă și a prevăzut tendințele de dezvoltare ale cercetării privind reducerea emisiilor de carbon din industria textilă. Rezultatele cercetării au indicat că, începând cu 2012, volumul studiilor de cercetare privind emisiile de carbon din industria textilă a înregistrat o creștere exponențială. Rezultatele cercetării au fost publicate în principal în reviste de științe ale mediului și de sustenabilitate, în timp ce revistele tradiționale din domeniul textil au înregistrat un volum mai redus de publicații, ceea ce sugerează că cercetarea interdisciplinară și multidisciplinară privind emisiile de carbon din industria textilă a rămas relativ redusă, calitatea cercetării necesitând îmbunătățiri. Dezvoltarea tehnologiilor de producție ecologice și a modelelor de economie circulară a influențat și a promovat transformarea ecologică a industriei textile, orientând-o către o eră a textilelor cu emisii reduse de carbon.

Cuvinte-cheie*: industria textilă, emisii de carbon, amprenta de carbon, analiza vizualizării, era textilelor cu emisii reduse de carbon*

INTRODUCTION

Carbon emissions from manufacturing industries have become an important area of focus within global climate change research [1–3], with the textile sector receiving increasing attention due to its significant environmental footprint, encompassing production process carbon emissions, product life cycle carbon footprints, clean production technologies, carbon reduction strategies, and green supply chain management [4]. Identifying and analysing textile industry carbon reduction research pathways to achieve green transformation and sustainable development of the textile industry represented a critical issue in the current global transition of the textile industry from high-carbon emissions to low-carbon development stages [5, 6]. Textile industry carbon emissions management proved essential for both industrial green upgrading and environmental protection [7]. Following nearly four decades of development, textile industry carbon emissions research has established a relatively comprehensive research framework [8, 9]. As global climate change pressures intensified and environmental policies became increasingly stringent [10–12], the textile industry needed to undergo technological transformation to address carbon reduction and green development challenges [13–15]. Within this context, textile enterprises, research institutions, and related organisations were required to appropriately utilise carbon emissions management approaches to reduce environmental impacts, enhance green competitiveness, and address climate risks [16–18]. Teixeira (2025) highlighted the importance of financial mechanisms and policy instruments in supporting industrial decarbonization efforts [19], while Li (2025) further demonstrated that green credit policies can significantly influence the corporate value of high-polluting enterprises [20]. These findings provide valuable insights for the textile industry's carbon management and inter-regional collaboration.

In the practical application of the textile industry carbon reduction, numerous technological approaches were employed to improve the environmental performance of textile manufacturing, including carbon footprint accounting and clean production technologies [21, 22]. Among these, carbon emissions monitoring technology was recognised as an important means for enhancing textile industry environmental management and served as the technological foundation for achieving the green transformation of the textile industry [23, 24]. Advanced technologies, including artificial intelligence, have shown promising potential in enhancing industrial sustainability and emission monitoring [25], offering new opportunities for precision carbon management in textile manufacturing. Furthermore, the waste-to-energy-coupled systems investigated by He and Qu (2025) provide a strategic framework for textile industrial parks to improve grid resilience and energy efficiency by converting manufacturing by-products into sustainable power for these high-demand digital infrastructures [26].

Literature analysis serves as an important approach for investigating carbon emissions development in manufacturing sectors and constitutes a tool for understanding the frontiers of industrial carbon reduction research. Through literature analysis, the research status of the textile industry carbon emissions field could be understood, future development trends predicted, and related fields explored and developed [27]. In literature research, the emergence or decline of various publications was consistently related to breakthroughs achieved in the field or significant events occurring in related areas. For instance, the signing of the Kyoto Protocol in 1997 directly promoted the development of carbon emissions research, leading to the emergence of substantial research related to carbon accounting and emission reduction technologies in the textile carbon emissions field, with research outcomes proliferating continuously. Similarly, the signing of the Paris Agreement in 2015 promoted research in areas such as low-carbon textiles, green manufacturing, and circular economy, with extensive textile industry carbon emissions research related to climate change response and green development emerging.

As carbon peak and carbon neutrality goals were implemented more deeply, the volume of related literature continued to grow and became increasingly diversified [20, 28, 29]. These phenomena clearly demonstrated that literature analysis could effectively capture hotspot issues in textile industry carbon emissions research and provide effective pathways for addressing current environmental problems [30]. Within environmental science and sustainable development research fields, the textile industry's carbon emissions represented an important discipline that combined environmental theory with practical applications. Textile industry carbon reduction constituted an important research area within environmental science. Unlike traditional environmental research, Hasanbeigi and Price (2015) noted that modern textile industry carbon emissions research relied more heavily on developments in environmental science, data science, and clean technologies [31]. Facing complex textile supply chains and diverse emission reduction requirements, the textile industry's carbon emissions management could be optimised through precise and systematic approaches [32]. Based on carbon data analysis, various environmental problems could be diagnosed, providing optimal solutions for textile enterprises to reduce carbon emissions, improve environmental performance, and enhance green competitiveness.

Due to the rapid development of computers and the internet, bibliometrics has experienced substantial advancement and has been widely applied in disciplines including environmental science, sustainable development, clean production, carbon management, and climate change [33]. Rousseau and Rousseau (2021) employed bibliometric indicators, utilising improved journal impact factor hierarchical regional assignment methods whilst introducing contribution rate indicators for differently ranked authors, establishing mathematical models for quantitative evaluation of textile industry carbon emissions papers [34]. This provided a new evaluation method for textile industry environmental management work that could complement peer review processes. Daraio and Bonaccorsi (2017) comprehensively investigated the developmental status of textile industry environmental impact fields, providing comprehensive descriptions of textile industry carbon emissions research fields through combined quantitative and qualitative research methods [35]. Moazzem et al. (2021) employed bibliometric methods to examine and analyse the development of textile industry life cycle assessment research [36]. Through basic statistical analysis and co-citation network analysis of literature samples, they discovered that the latest hotspots in textile industry carbon emissions research concentrated on carbon footprint assessment and green supply chains, effectively demonstrating the characteristics of textile industry carbon emissions research through bibliometric approaches [37–39]. This clearly indicated that bibliometrics represented a continuously developing literature analysis method that was widely welcomed by scholars in the textile industry and environmental science.

DATA SOURCES AND RESEARCH METHODS

Data sources

All data utilised in this study were derived from the Web of Science Core Collection (SCI-E and SSCI). The data retrieved from the platform primarily comprised abstracts, keywords, citations, authors, research institutions, countries and regions, and download records of papers related to carbon emissions in the textile industry. It should be particularly noted that when downloading and analysing the data, the data from Hong Kong and Taiwan were not merged with mainland China's data for analysis, but were instead analysed separately by classification. A total of 349 data records were downloaded, with the data acquisition date being 27 June 2025.

Research methods

This study was based on bibliometric methods, primarily utilising CiteSpace literature data visualisation software developed by Drexel University in the United States for analysis. Following the approach established by Merigó et al. (2015) [40], the specific analytical methodology for this research was constructed as follows:

Search terms: "textile carbon emissions" OR "textile industry carbon footprint" OR "carbon emissions textile" OR "textile sustainability carbon"; Time period: "2000–2025"; Data source: Web of Science. CiteSpace's relationship strength algorithms primarily include the Cosine algorithm, Jaccard algorithm, and Dice algorithm, as detailed below:

Cosine algorithm:

$$\text{Cosine}\,(c_{ij}, s_i, s_j) = \frac{c_{ij}}{\sqrt{s_i s_j}} \tag{1}$$

Jaccard algorithm:

$$\text{Jaccard}\,(c_{ij}, s_i, s_j) = \frac{c_{ij}}{s_i + s_j - c_{ij}} \tag{2}$$

Dice algorithm:

$$\text{Dice}\,(c_{ij}, s_i, s_j) = \frac{2\,c_{ij}}{s_i + s_j} \tag{3}$$

Studies typically use the Cosine algorithm, which normalises the values between 0 ~ 1, with c_{ij} being the number of occurrences of i and j, s_i being the number of occurrences of i, and s_j being the number of occurrences of j, and which can be expressed based on the generalised similarity index as follows:

$$s_G(c_{ij}, s_i, s_j, 1) = \frac{2\text{Jaccard}\,(c_{ij}, s_i, s_j)}{\text{Jaccard}\,(c_{ij}, s_i, s_j) + 1} = \text{Dice}\,(c_{ij}, s_i, s_j) \tag{4}$$

In this paper, we use Cite Space software to implement these similarity algorithms and analyse them computationally using both inter- and intra-time slices.

REVIEW OF TEXTILE CARBON EMISSIONS RESEARCH

Trends in the number of textile carbon emissions research publications

According to figure 1, which presents a time series analysis of the annual publication volume in textile industry carbon emissions journals (2000–2025), the temporal trends in publication numbers (2000–2025) could be constructed. Several important characteristics were observed from the graph:

• Developmental stage characteristics: Embryonic period (2000–2012): Research commenced relatively late, with extremely limited publication volumes. The annual number of published papers remained essentially between 0 and 3 articles, indicating that this field had not yet received widespread attention from the academic community.

• Gradual growth period (2013–2018): Publication volumes began to increase, growing progressively from 2 articles in 2013 to 12 articles in 2018. The annual growth remained relatively modest, reflecting emerging research interest in the field.

• Rapid development period (2019–2024): Publication volumes experienced explosive growth, particularly escalating rapidly from 12 articles in 2019 to a peak of 69 articles in 2024. This period demonstrated the most significant growth, with 48 articles published in 2021 and reaching a historical high point in 2024.

• Decline and adjustment period (2025): Publication volumes decreased to 44 articles, which may have been related to the data collection timepoint or reflected a natural adjustment in research intensity.

• Overall trend analysis: The general pattern exhibited exponential growth, particularly with accelerated growth after 2019. This trend was closely related to increased global attention to climate change, the establishment of carbon neutrality targets, and heightened policy and academic attention towards the textile industry as a high-energy-consuming and high-pollution sector. The rapid increase in research intensity reflected the growing importance and urgency recognised in this field.

Analysis of author collaboration and co-citation networks

The examination of author collaboration networks is a critical approach for assessing research capabilities and evaluating the development of an academic

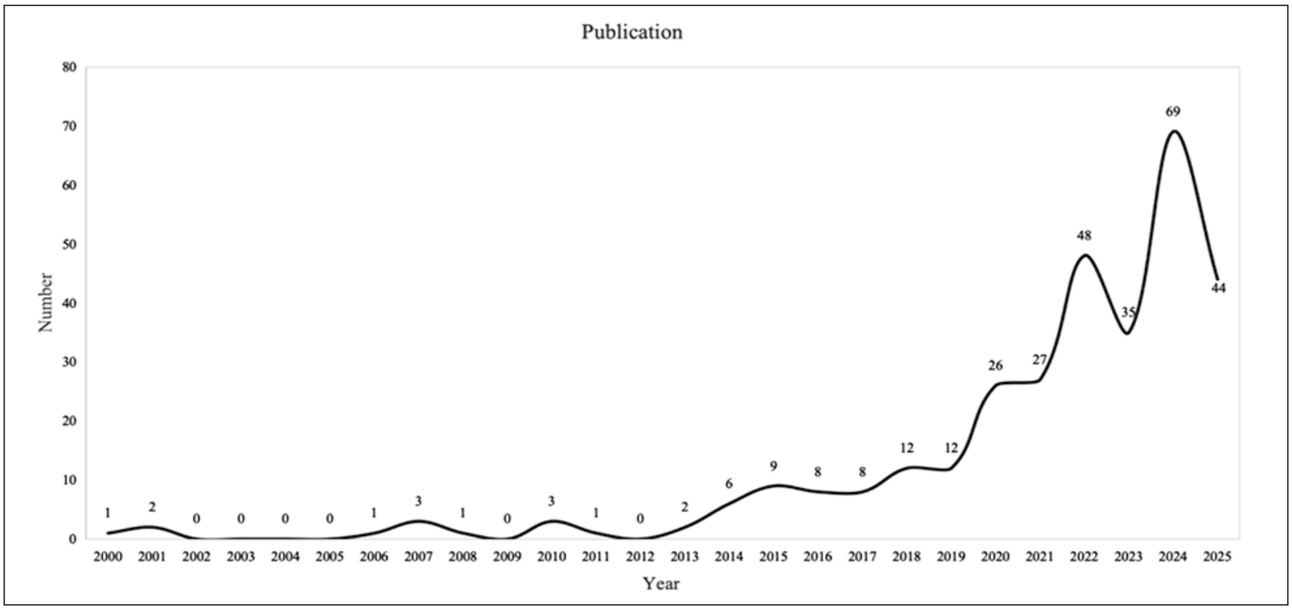

Fig. 1. Annual publication trend

field. Based on the visualisation of author collaboration networks generated using CiteSpace software (time span: 2005–2023), the following salient characteristics were observed within the field of carbon emissions in the textile industry:

• Characteristics of core collaborative groups: The network diagram revealed the formation of several distinct collaborative groups within this research domain. Most notably, a prominent collaboration network centred around Nimtmaki K (2020) was identified, positioning this scholar at the core of the network with numerous intensive cooperative ties. Similarly, researchers such as Li Lin G (2018), Peters G (2021), and Cheng Y (2021) emerged as key nodes of collaboration, constituting the primary research force in the field.

• Temporal evolution: The time-labelled nodes indicated a clear temporal evolution of the collaboration network. In the early phase (2012–2017), cooperation was predominantly centred around scholars such as Dahlbo H (2017) and Kanemoto K (2012). In the more recent period (2020–2023), the network expanded to include researchers such as Nimtmaki K, Luo Y (2022), and Chen S (2023), thereby forming a more complex and densely connected collaborative structure. This trend reflected the rapid development of the field and the deepening of academic cooperation.

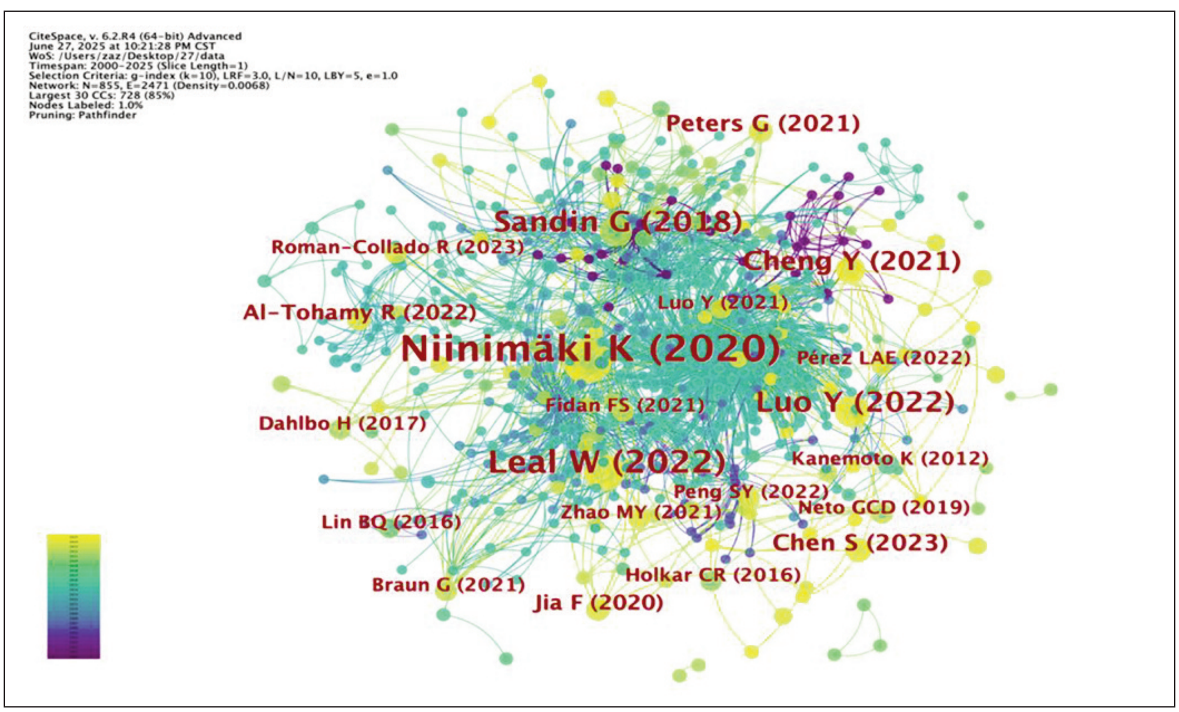

Fig. 2. Co-citation network of references

• Network density: The visualisation demonstrated a relatively high connection density, suggesting that collaboration among scholars in this domain was active. In particular, a highly interconnected research cluster centred on Nimtmaki K was evident in the core area of the network. Dense linkages among these nodes reflected frequent academic exchanges and cooperation. Additionally, scholars such as Roman-Collado R (2023) and Al-Tohamy R (2022) maintained multiple connections with the core network, further contributing to its cohesion.

• Distribution of research groups: Beyond the principal collaborative clusters, the network also exhibited a multi-layered structure. Scholars such as Peters G (2021), Luo Y (2022), and Leal W (2022) formed secondary collaboration centres that remained connected to the core network while maintaining relatively independent research orientations. On the periphery, researchers such as Holkar CK (2016) and Jia F (2020), although less connected, contributed to the diversity of research within the field.

• Overall assessment: The author collaboration network displayed a centralised structure with Nimtmaki K at its core, alongside a multi-centre, multi-layered distribution pattern. This suggested that the field of carbon emissions research in the textile industry had developed into a relatively mature international academic community. Core authors, through sustained collaborative efforts, made significant contributions to the theoretical development and practical applications in the field. Furthermore, the network's temporal progression clearly illustrated a trajectory from dispersed research efforts towards more centralised collaboration.

Prominent research themes based on keyword co-occurrence

The frequency of keyword co-occurrence provided a direct and effective means of illustrating the research areas and core content within a specific discipline. In this study, the keyword analysis function of CiteSpace was employed to construct a keyword co-occurrence network, thereby outlining the principal research hotspots in the field of carbon emissions within the textile industry. The knowledge domain map of the keyword co-occurrence network, generated by CiteSpace (parameters: time span 2000–2025; node type: keyword; network density: 0.0158), presented four major thematic clusters. These clusters centred on themes such as carbon emissions accounting, the impact of the textile industry, environmental assessment, and sustainable development.

Cluster #1 (Red Zone): Centred on the core nodes "carbon emissions" and "CO_2 emissions", this cluster predominantly encompassed research on the direct measurement and accounting of carbon emissions. Representative keywords included "greenhouse gas emissions", "carbon footprint", and "emissions". This cluster focused on the quantitative assessment and calculation methodologies related to carbon emissions in the textile industry, and represented the foundational core of research in this domain.

Cluster #2 (Green Zone): This cluster was organised around the core node "textile industry", linking keywords such as "textile", "consumption", "international trade", and "environmental impact". It emphasised systemic research across the textile value chain, highlighting carbon emissions throughout the entire process from production to consumption. This reflected the complexity of the textile industry as a globalised sector.

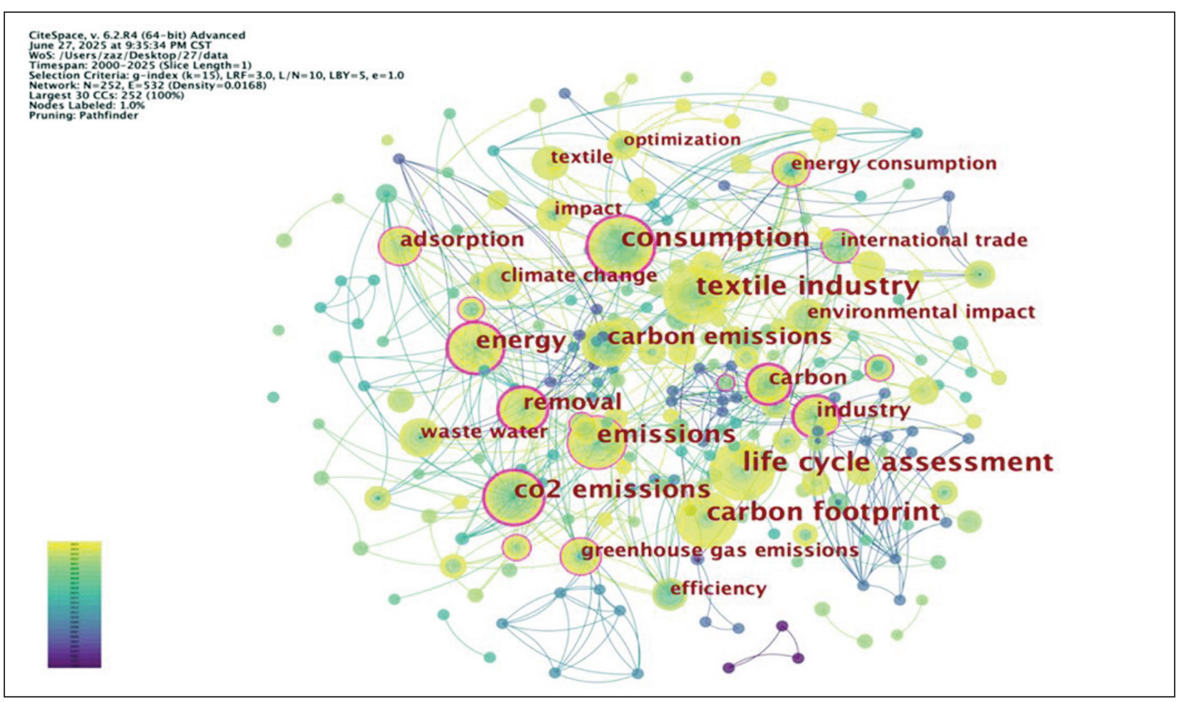

Fig. 3. Keyword co-occurrence map

Cluster #3 (Blue Zone): Centred on “life cycle assessment”, this cluster represented the methodological direction of environmental evaluation. Key associated terms included “impact”, “industry”, “energy consumption”, and “efficiency”. The cluster underscored system-level approaches to environmental assessment and highlighted studies on the environmental footprint of the textile sector from a full life cycle perspective.

Cluster #4 (Yellow Zone): With “climate change” and “optimisation” as its central nodes, this cluster encompassed topics related to climate change mitigation, wastewater treatment, removal technologies, and adsorption processes. It reflected a shift in textile industry carbon emission research towards solution-oriented approaches and sustainable development strategies.

Interdisciplinary integration: The network diagram revealed dense interconnections among the clusters. Notably, the node “energy” functioned as a critical bridging point linking multiple clusters, underscoring the central role of energy consumption in the field of textile carbon emissions. In addition, the central positioning of nodes such as “consumption” and “environmental impact” highlighted the importance of end-user behaviour and environmental evaluation in this research area.

Overall assessment: The keyword co-occurrence network demonstrated a clear shift in textile industry carbon emissions research from singular emission accounting to integrated evaluations across the entire value chain and life cycle. The close interconnections among clusters further illustrated the interdisciplinary nature and systemic focus that had become characteristic of this evolving research field.

Keyword clustering analysis

Keywords represented the core content of academic publications and commonly occurring terms within a study. They provided an efficient and accurate means of understanding the primary focus of the literature, thereby serving as a crucial element in tracing the evolution of research on carbon emissions in the textile industry. This study conducted a keyword clustering analysis, as illustrated in the figure.

Using CiteSpace’s clustering function, eleven primary research clusters were identified (parameter settings: modularity Q = 0.6736; mean silhouette score S = 0.8316), indicating a well-structured clustering outcome with high internal homogeneity.

The keyword clustering analysis revealed the current research hotspots and thematic directions in textile industry carbon emissions research, which mainly included the following key domains:

• Core research on carbon emissions: Cluster #0, labelled “carbon intensity”, emerged as the largest cluster and was located at the centre of the network. This cluster primarily focused on the measurement of carbon intensity, accounting methodologies, and the assessment of emission reduction potential, reflecting the central concerns of this research field.

• Technological innovation and intelligent analysis: Clusters #1 “machine learning” and #2 “structural path analysis” reflected the extensive application of modern data analytics and econometric methods in textile carbon emission studies. These clusters represented the increasing trend toward technological sophistication and intelligent analysis in research methodologies.

• Environmental impact of chemicals and dyes: Cluster #3 “cationic dyes” highlighted environmental

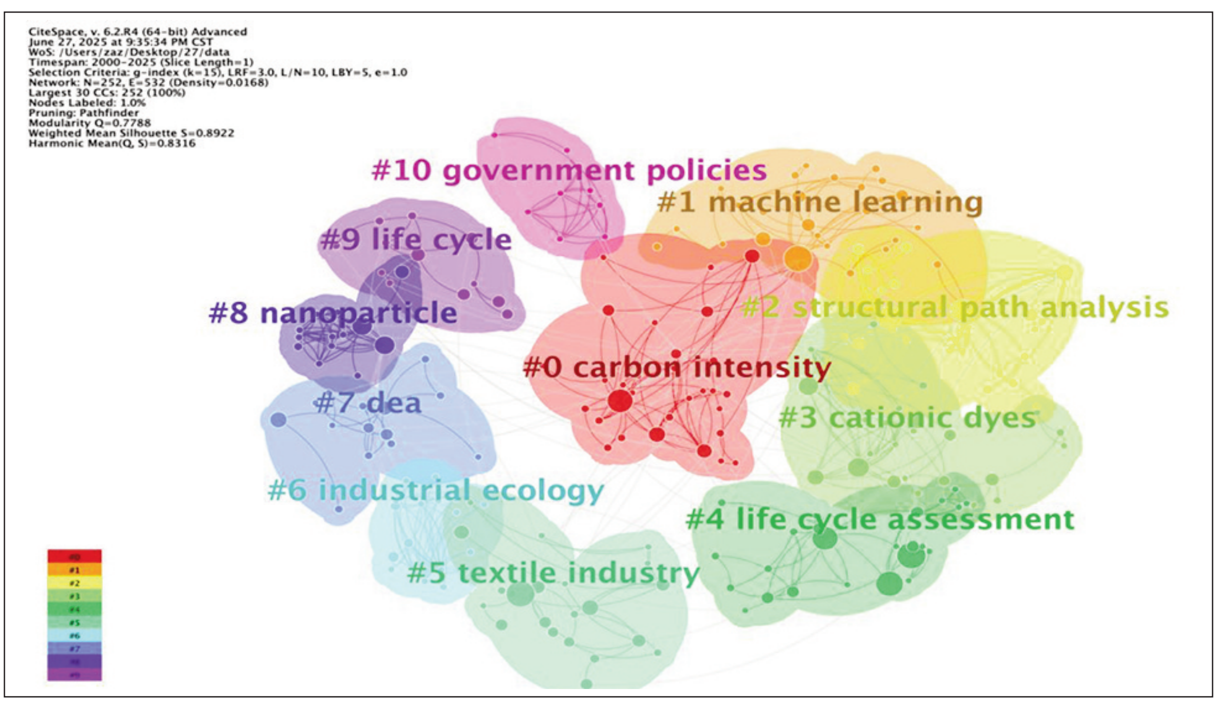

Fig. 4. Keyword clustering mapp

concerns related to the use of chemicals during textile production, indicating a research perspective focused on emission control at the production stage.

• Life cycle assessment approaches: Clusters #4 "life cycle assessment" and #9 "life cycle" emphasised the importance of systematic environmental assessment methods. These clusters illustrated a research orientation encompassing entire processes and supply chains, aligning with holistic sustainability principles.

• Industrial ecology and circular economy: Clusters #5 "textile industry" and #6 "industrial ecology" demonstrated a macro-level perspective on the textile sector's carbon emissions, concentrating on material and energy flows, as well as resource circulation between industries from an ecological systems viewpoint.

• Emerging technology applications: Cluster #7, "DEA (data envelopment analysis)" and cluster #8 ", nanoparticles" represented studies on efficiency assessment and the application of nanotechnology in the pursuit of low-carbon development within the textile industry.

• Policy and governance research: Cluster #10 "government policies" reflected investigations into the influence of policy frameworks on carbon emissions in the textile industry, underscoring the role of governance mechanisms in driving sectoral emission reductions.

The visualisation clearly depicted the research hotspots currently attracting scholarly attention. The spatial distribution and connection strength between clusters illustrated the interrelated nature of various research themes. It was evident that research on carbon emissions in the textile industry had increasingly focused on quantitative assessment, technological innovation, and policy governance. This indicated an interdisciplinary orientation combining theoretical inquiry with practical applications, and technical methods with policy tools. Moreover, it underscored the field's transition from examining isolated environmental impacts to pursuing a comprehensive and systemic approach to sustainable development.

Evolution of research hotspots and future trends

Based on the selection of "Keyword" as the node type and the use of the "Burstness" function in CiteSpace, the top 25 keywords with the highest burst intensities were identified, as shown in the figure. A higher burst intensity indicated a period of heightened academic activity and research interest. By analysing the temporal evolution of research hotspots in the field of textile industry carbon emissions between 2000 and 2025, distinct developmental stages and emerging trends were revealed.

• Initial exploration stage (2001–2014): During this period, research was primarily focused on foundational concepts and methodological development. "Energy consumption" began to surge in 2001 with a burst intensity of 2.02, continuing until 2017, which reflected the early interest in energy use within the textile sector. The keyword "reuse" exhibited a burst in 2008 with an intensity of 1.33, indicating the initial diffusion of circular economy concepts. "Consumption"

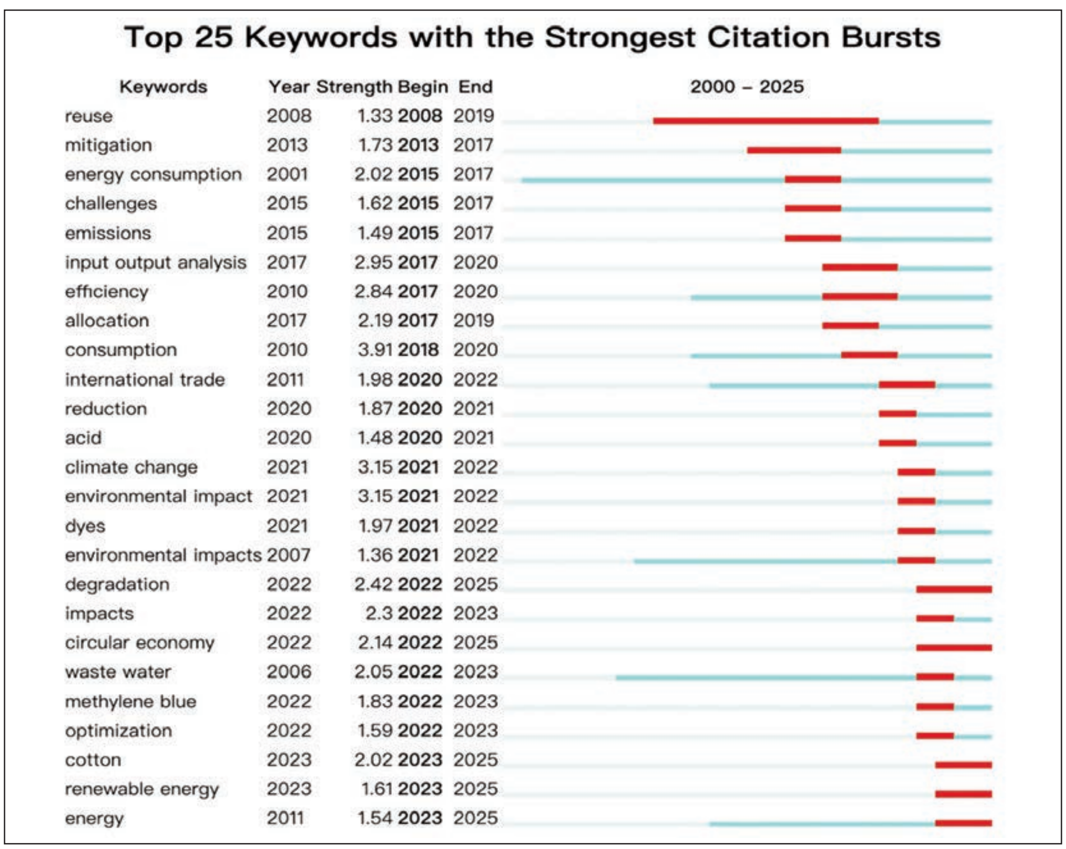

Fig. 5. Keyword burst map

surged in 2010 with a burst intensity of 3.91, signifying a research shift from the production side to consumption-related emissions.

• Rapid development stage (2013–2020): Between 2013 and 2020, keywords such as "mitigation", "challenges", "emissions", "efficiency", and "allocation" experienced notable bursts. Notably, "consumption" reached its highest burst intensity of 3.91 in 2018. "Input-output analysis" and "efficiency" both surged in 2017, with intensities of 2.95 and 2.84, respectively. Research during this period demonstrated increasing systematisation and methodological diversification, marking a transition from isolated issues to complex system-level analysis within the field.

• Mature development and frontier breakthrough stage (2020–2025): Post-2020, research hotspots reflected clear policy orientation and technological innovation. "Climate change" and "environmental impact" both experienced bursts in 2021, each with an intensity of 3.15, highlighting the influence of global climate policy on academic inquiry. The year 2022 represented a pivotal point, with simultaneous bursts in several keywords such as "degradation", "circular economy", "wastewater", "methylene blue", and "optimisation". Among these, "degradation" recorded the highest burst intensity of 2.42, indicating growing interest in environmental remediation and waste management technologies.

• Emerging hotspots and future directions (2023-2025): Since 2023, research interests have increasingly centred on technological applications and sustainable development. "Cotton" and "renewable energy" began to surge in 2023, with burst intensities of 2.02 and 1.61, respectively, both projected to remain active through 2025. Although "energy" initially surged in 2011, it exhibited renewed interest in 2023, with a burst intensity of 1.54, reaffirming its persistent significance in textile-related carbon emission research.

Analysis of developmental trends: The overall evolution of research in this domain followed a trajectory from "problem identification" to "systemic analysis" and ultimately to "solution-oriented approaches". Early studies emphasised energy consumption and waste treatment at individual production stages. The mid-stage progressed towards system-wide life cycle assessment and policy evaluation. In recent years, research has increasingly focused on technological innovation and the exploration of circular economy models. The simultaneous surge of multiple keywords post-2022 suggested a rapid maturation of the field and an urgent need for practical applications.

This evolutionary trajectory demonstrated that carbon emission research in the textile industry had transitioned from theoretical exploration to practical implementation. Future research was expected to place greater emphasis on integrated studies involving technological innovation, policy coordination, and industrial transformation. In particular, the integration of renewable energy, circular economy strategies, and intelligent emission reduction technologies was likely to remain at the forefront of academic inquiry in the years ahead.

Network analysis of core research institutions

In addition, this study conducted a clustering analysis of the core research institutions involved in the study of carbon emissions in the textile industry, as illustrated in the figure (parameter settings: modularity Q = 0.6736; average silhouette value S = 0.8316). The institutional collaboration network revealed a multipolar international research structure, predominantly centred in China, Europe, and North America. The network demonstrated clear geographical clustering and strong characteristics of transnational collaboration.

Chinese research cluster: The core institutions included Zhejiang Sci-Tech University, Donghua University, Jiangnan University, Xiamen University, Peking University, Minjiang University, and major research institutes such as the Chinese Academy of Sciences. These institutions formed a closely-knit collaborative network focused on carbon emission accounting, life cycle assessment, and emission reduction technologies in the textile industry. This underscored China's leading role in environmental research within the global textile sector, reflecting its status as a major textile-producing country.

European research cluster: Centred around Nordic universities such as Aarhus University and Chalmers University of Technology, this cluster also included prominent institutions like the French National Centre for Scientific Research (Centre National de la Recherche Scientifique, CNRS). The European group demonstrated a distinct advantage in environmental policy analysis, sustainability assessment, and the study of the environmental impacts of international trade. This reflected the European Union's leadership in environmental governance and sustainable development policy.

North American research node: The Lawrence Berkeley National Laboratory, under the United States Department of Energy, played a pivotal role in energy systems analysis and carbon emission modelling. This node highlighted North America's research strength in environmental science and technological innovation.

Emerging research actors: Institutions such as Adana Alparslan Turkes Science & Technology University in Türkiye and Guangdong University of Technology in China represented the expanding international participation in this field. Their involvement illustrated the increasing engagement of emerging economies in global environmental research.

Transnational collaboration characteristics: The network visualisation revealed dense transnational linkages, with particularly close collaborations between China and Europe, as well as between China and the United States. The presence of multinational research frameworks, such as the National Institute of Technology (NIT) system, further illustrated the institutionalisation of international cooperation. This pattern of collaboration underscored the inherently

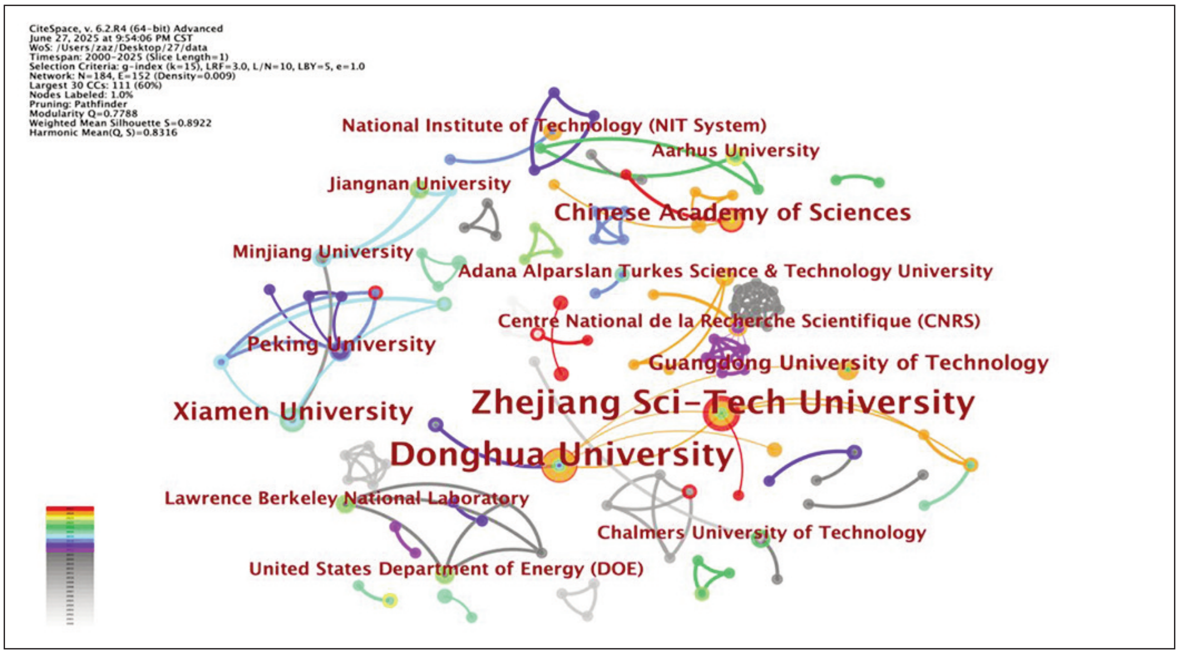

Fig. 6. Institutional collaboration map

global nature of textile industry carbon emissions and the necessity for coordinated international research efforts.

Integration of research and industrial application: The network encompassed both traditional academic institutions and industrial technology research platforms, highlighting the field's transition from theoretical exploration to practical implementation. The diversification of institutional partnerships provided crucial support for the industrial application of carbon reduction technologies in the textile sector.

In summary, the density and strength of connections within the network indicated the emergence of a relatively mature international collaborative system in textile industry carbon emission research. This framework offered a robust scientific foundation and cooperative platform to support the green transformation of the global textile industry and the achievement of carbon neutrality goals.

Timeline clustering analysis of keywords

This study also conducted a timeline clustering analysis of key information, resulting in the visualisation shown in the figure. In bibliometric analysis, a timeline view illustrates the chronological development and interconnections among various research topics. The larger the co-citation cluster, the higher its centrality within the network. The timeline diagram clearly depicted the evolutionary trajectory of research on carbon emissions in the textile industry from 2000 to 2025, as well as the developmental pathways of major research themes.

As shown in the figure, clusters #0 to #4 exhibited the highest centrality. These clusters corresponded to carbon intensity, machine learning, structural path analysis, cationic dyes, and life cycle assessment, respectively. These topics maintained high levels of academic attention throughout the entire time period, indicating their foundational role in shaping the core content and methodological approaches of textile industry carbon emission research.

- Early exploration stage (2000–2010): Research during this phase primarily focused on the establishment of fundamental concepts and the identification of key problems. Core topics included energy consumption, greenhouse gas emissions, and CO_2 emissions. The importance of carbon intensity began to emerge during this period, laying the groundwork for subsequent in-depth studies. Environmental management topics such as wastewater removal also attracted early attention.
- Methodological development stage (2010–2018): Specialised methodological approaches such as life cycle assessment and structural path analysis became increasingly mature, resulting in a more comprehensive analytical framework. Systemic research themes, including consumption, international trade, and carbon emissions, were significantly developed. The introduction of machine learning techniques marked a technological upgrade in methodological applications within the field.
- System integration stage (2018–2022): This period saw the emergence of integrated research themes, such as the textile industry, industrial ecology, and data envelopment analysis (DEA). Notably, concepts such as carbon footprint, environmental impact, and climate change experienced strong growth after 2020, reflecting a shift in the field towards system-oriented and policy-driven approaches.
- Frontier innovation stage (2022–2025): Emerging research topics such as circular economy, government policies, and optimisation demonstrated robust growth in recent years. Technological themes, including degradation and methylene blue, also appeared

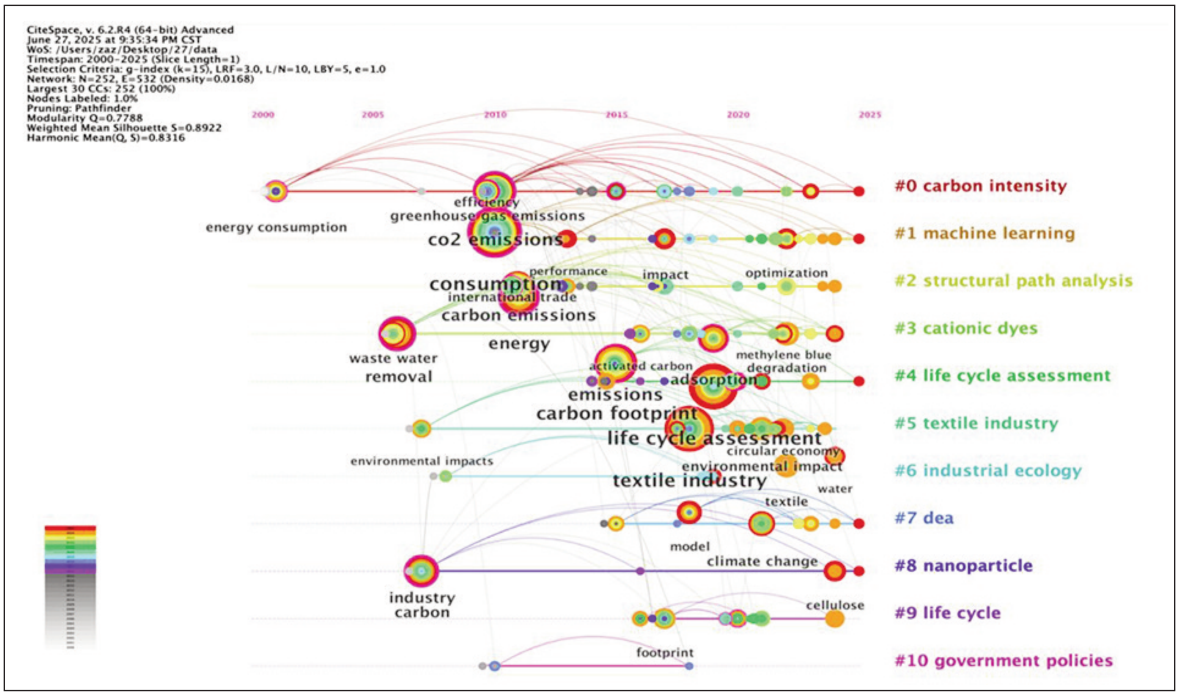

Fig. 7. Cluster timeline

during this stage, indicating a transition from theoretical research to technological application and innovation.

Cross-temporal persistent themes: Keywords such as textile, nanoparticle, and life cycle persisted throughout the entire study period, suggesting their sustained research value. In particular, life cycle research evolved from an early-stage methodological exploration into a central analytical framework underpinning the field.

Future research directions: Based on the trajectory shown in the timeline, it was anticipated that future research would focus on circular economy models, intelligent optimisation technologies, and collaborative policy mechanisms. These areas were expected to drive the evolution of carbon emission research in the textile industry from isolated environmental assessments towards integrated sustainable development solutions. Such advancements would provide a scientific foundation for promoting the green transformation of the textile sector and achieving carbon neutrality goals.

Analysis of disciplinary integration and interdisciplinarity

The study of carbon emissions in the textile industry involved extensive interdisciplinary integration. In this research, the CiteSpace software was used to generate a subject co-occurrence map to examine the connections between textile industry carbon emissions research and other academic disciplines, as illustrated in the figure. The dual-map overlay clearly demonstrated the interdisciplinary nature of this research area, highlighting the necessity of integrating multiple fields to achieve more comprehensive and robust outcomes.

In the figure, the coloured lines represent citation paths and knowledge flows among various disciplines. The following disciplinary clusters showed the strongest associations with textile industry carbon emissions research:

- Engineering and technology cluster: This cluster originated from disciplines such as physics, materials science, and chemistry (#5 PHYSICS, MATERIALS, CHEMISTRY) and extended to areas including plant science, biology, genetics, genetic engineering, and biotechnology (#10 PLANT, BIOLOGY, GENETICS, BIOCHEMISTRY, BIOTECHNOLOGY), as well as environmental science, ecology, and geography (#11 ENVIRONMENTAL, TOXICOLOGY, NUTRITION). The concentration of knowledge flow in this cluster reflected the developmental trajectory from material science foundations to applications in biotechnology and environmental assessment within the textile sector.
- Medical and health cluster: Fields such as health sciences, nursing, and medicine (#6 HEALTH, NURSING, MEDICINE), along with dermatology, dentistry, and surgery (#9 DERMATOLOGY, DENTISTRY, SURGERY), contributed to the understanding of the impact of textile-related carbon emissions on human health. This was particularly evident in research concerning occupational health and environmental health risk assessment.
- Economic and management cluster: The intersection of psychology, education, health, and sociology (#7 PSYCHOLOGY, EDUCATION, HEALTH, SOCIAL) highlighted the socio-economic dimensions of textile carbon emissions research. This included investigations into consumer behaviour, policy-making, and social impact assessments, underscoring the need for research that addresses broader societal implications.

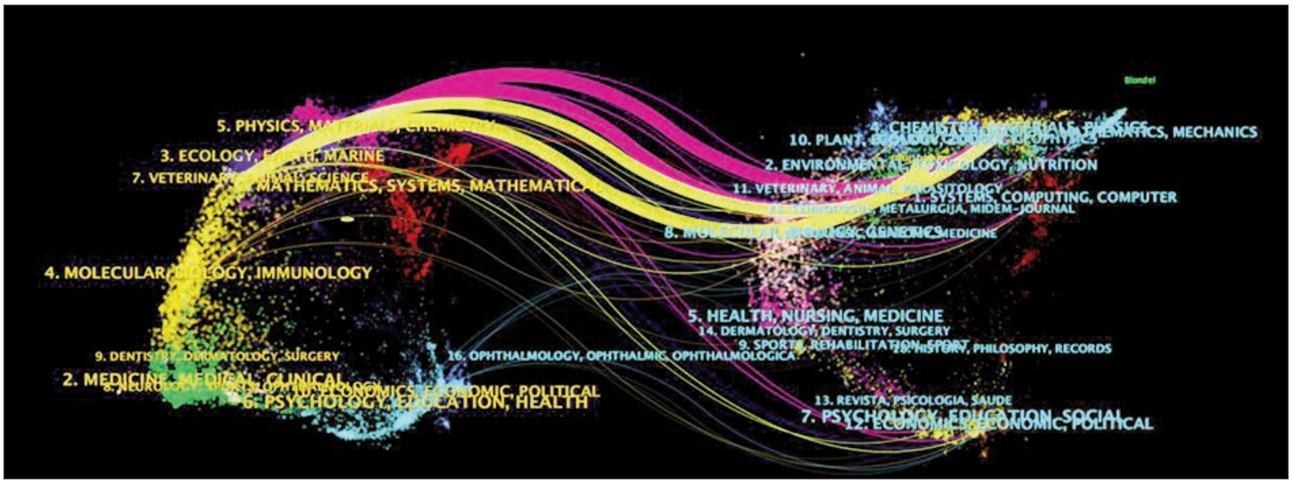

Fig. 8. Journal dual-map overlay

• Ecological and environmental cluster: This cluster included ecology, earth sciences, and marine sciences (#3 ECOLOGY, EARTH, MARINE), integrated with veterinary science and zoology (#8 VETERINARY, ANIMAL, SCIENCE). It represented comprehensive assessments of carbon emissions' impacts on ecosystems – spanning terrestrial, marine, and animal health perspectives.

• Molecular biology cluster: Disciplines such as molecular biology and immunology (#4 MOLECULAR, BIOLOGY, IMMUNOLOGY) provided essential theoretical foundations for exploring the biological mechanisms of textile-related carbon emissions, environmental toxicology evaluations, and the development of bioremediation technologies.

Knowledge flow characteristics: The figure revealed a clear trend of knowledge flow from foundational sciences to applied sciences and from isolated disciplines towards interdisciplinary integration.

Particularly notable was the active flow from core disciplines such as physics and chemistry to applied fields, including environmental science and biotechnology. This suggested a transition in carbon emission research within the textile industry from theoretical exploration to practical application.

In terms of disciplinary coupling strength, textile industry carbon emissions research exhibited the strongest associations with environmental science, materials science, and biotechnology. Connections with medical and health sciences, as well as social sciences, also continued to strengthen. This trend of multidisciplinarity reflects the complex nature of carbon emissions as an environmental issue, demanding integrated and holistic solutions. It also indicated that future research in this domain would increasingly prioritise cross-disciplinary collaboration and the application of systemic research methodologies.

CONCLUSION AND RECOMMENDATIONS

Based on a bibliometric analysis of textile industry carbon emissions research from 2000 to 2025, the field underwent a significant evolution from its nascent stage (2000–2012) to a period of rapid development (2019–2024). The volume of research increased dramatically after 2019, rising from an annual average of fewer than three publications to a peak of 69 in 2024. This surge reflected the strong influence of global climate policies and carbon neutrality targets on academic research agendas.

The research focus experienced a profound paradigm shift, transitioning from early investigations centred on energy consumption and waste management to a systematic carbon footprint evaluation framework. Key thematic areas emerged, including carbon accounting methodologies, innovations in clean production technologies, the construction of circular economy models, and the management of green supply chains. Methodologically, the field evolved from traditional statistical approaches to the application of advanced techniques such as machine learning, data envelopment analysis, and structural path analysis.

The pattern of international collaboration revealed a multipolar structure, with China playing a leading role alongside significant contributions from Europe and North America. In China, institutions such as Zhejiang Sci-Tech University, Donghua University, Jiangnan University, and the Chinese Academy of Sciences formed robust research networks. European clusters, particularly those led by Aarhus University and Chalmers University of Technology, demonstrated strong capabilities in environmental policy analysis. Meanwhile, North American institutions contributed significantly to energy system modelling and technological innovation. The field exhibited a high degree of interdisciplinary integration, extending beyond environmental and materials sciences to intersect deeply with biotechnology, information science, economics, and sociology. This reflected the complex and multifaceted nature of carbon emissions in the textile industry and the necessity of comprehensive, interdisciplinary solutions.

The evolution of research hotspots followed a clear trajectory: beginning with the establishment of foundational concepts and issue identification, progressing to systemic life cycle assessment and policy analysis, and advancing in recent years toward technological innovation and the exploration of circular economy models. Notably, after 2022, there was a marked increase in research focused on circular economy, wastewater treatment, and optimisation technologies, indicating a pivotal shift from theoretical exploration to practical application.

Future research should prioritise the following directions:

• Based on the current research status and development trend of carbon emissions in the textile industry, the future research direction should focus on technological innovation and interdisciplinary integration: at the technical level, it is necessary to develop digital carbon management technology based on the Internet of Things, big data and artificial intelligence to achieve accurate carbon footprint tracking throughout the life cycle, and promote the research and development and application of low-carbon new materials such as bio-based fibers and recycled fibers and energy-saving and emission reduction dyeing and finishing processes; In terms of discipline integration, we should strengthen in-depth collaboration between environmental science, materials science, data science, economics and other disciplines, promote the cross-publication of traditional textile journals and environmental science journals, and improve the quality of cross-disciplinary research. At the level of supply chain optimisation, build a digital management platform for green supply chains based on blockchain technology, deepen the circular economy model, and explore the high-value utilisation of textile waste. In terms of policy and standardisation construction, establish a unified carbon emission accounting methodology and international standards for the textile industry, and design effective carbon emission reduction incentive mechanisms. In the cutting-edge application field, expand the research on carbon management on the consumer side, explore regional differentiated emission reduction paths, and the application prospects of carbon capture, utilization and storage technology in the textile industry, and finally form a comprehensive research system covering technological innovation, policy guidance, standards and norms, and market mechanisms, providing all-round scientific support for the green transformation of the textile industry and the realization of carbon peak and carbon neutrality goals.

• Technological innovation: Emphasis should be placed on the integration of renewable energy, application of nanomaterials, development of intelligent emission reduction technologies, and advancement of digital monitoring systems.

• Systemic transformation: Greater efforts are needed to embed circular economy principles across the entire textile value chain, from fibre production to garment recycling, aiming to establish a closed-loop system.

• Policy frameworks: It is essential to develop more comprehensive carbon accounting standards and mechanisms for policy coordination, ensuring effective integration between industrial and environmental policies.

• Through the deep integration of digital and green technologies, and the dual driving forces of technological and business model innovation, the textile industry may achieve a fundamental transformation from traditional high-carbon production to a low-carbon, high-efficiency model. This transition will provide strong scientific and practical support for the sustainable development of the global textile sector and the realisation of carbon neutrality goals.

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