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Production Process Modeling in Textile Industry via Knowledge Graph and Graph Spatiotemporal Attention Networks

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Abstract: The textile industry is a pillar of the national economy. Due to the fragmentation of production factors, insufficient capture of spatiotemporal characteristics, and slow response to dynamic adjustments, current clothing production faces problems such as inefficient process coordination and lagging dynamic scheduling. These issues manifest as a high proportion of waiting time for process connection and low equipment utilization. The study combines knowledge graph with graph spatiotemporal attention network to construct a production process model for textile and clothing industry and conducts research on production process prediction. The results indicated that the average accuracy of the proposed model kept rising and finally neared 1.00, which was notably superior to that of other comparative models. The average precision of the proposed model ultimately exceeded 0.95, accurately matching the process collaboration requirements for multi-variety production. For the proposed model, its mean absolute error remained stable within a range of 0.15. The prediction accuracy of different production processes ranged from 1.87 to 2.36, with a root mean square error of 2.87 to 3.52 and an R^2 of 0.91 to 0.95. The prediction error was reduced by 33.8%-49.2%. The research method can effectively model and predict the clothing production process, providing accurate and efficient decision support for the textile industry's clothing production, and improving production efficiency and quality.

Keywords: Textile industry, clothing production, knowledge graph, graph spatiotemporal attention network, gated recurrent unit.

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1. Introduction

Nowadays, as the textile industry advances at a swift pace, the clothing production process is growing increasingly complex, and conventional production management approaches can no longer satisfy the demands for efficient and accurate production (Li et al., 2024). The knowledge graph, as an effective method for organizing and representing knowledge, has shown great potential in knowledge management across various industries. Graph spatiotemporal attention networks have been widely used in the field of prediction due to their powerful processing capabilities for spatiotemporal information (Munoz and Yilan, 2025). In recent years, some studies have applied knowledge graphs or graph neural networks to the manufacturing industry, but deep integration applications in the textile and clothing production fields remain relatively scarce (Jung et al., 2023). In response to the problem of noise amplification and difficulty in capturing real facts caused by dynamic features of entity relationships in time knowledge graphs with few shots, An et al. (2024) proposed a framework including a dynamic attention neighbor aggregator, which integrates an error perception feature extractor in meta learning. The experiment showed that it performed well under a few-shot setting, and the relevant indicators were significantly improved. Cui et al. (2024) proposed a graph spatiotemporal attention recurrent network method with a phase lag index to evaluate the degradation status of aircraft engine system equipment maintenance decisions. They constructed a spatiotemporal graph and combined it with a long short-term memory network with an attention mechanism to capture spatiotemporal features. The method was applied to cyber-physical systems, and the results showed good performance in remaining health life management and fault diagnosis. To investigate the impact of sewing and bonding techniques on the aesthetic, mechanical, and electrical properties of electronic textile packaging, Domskiene et al. (2023) used sewing, adhesive bonding, and other techniques to make samples and test their thickness and other properties. They found that cutting and sewing could obtain reliable packaging, and seam sealing affects electrical and deformation performance. Suitable connection methods need to be selected to ensure durability and safety. Yang et al. (2024) built a multi-objective optimization model and designed a dual population genetic algorithm to solve the problems of time imbalance and low balance rate in clothing sewing production line workstations. Taking the front panel of jeans as an example for simulation verification, the results showed that the smoothness index of the production line decreased to 8.43 and the balance rate increased to 89.06%, effectively solving the production balance problem. To solve the problem of making fashion products more competitive in price without compromising quality and innovation, Wahyuningsih et al. (2023) analyzed that new products such as accessories can be made by upgrading the recycling process through the use of pieced together waste in clothing production, improving raw material utilization and reducing production costs.

To address how to improve process efficiency in the clothing industry based on 5Ms resources, Fatima and Tufail (2023) collected data on product layout, conducted time motion research, and evaluated production line information to develop guidance plans. As a result, efficiency was increased by 10%, and the utilization of manpower and funds was also improved. In response to the lack of environmental impact, chromaticity, and retro effect evaluation in existing hazardous denim drying processes, Rahaman et al. (2024) tested alternative processes with different sodium hydroxide concentrations and heat treatment temperatures, and evaluated relevant indicators using environmental impact measurement software. The results showed that the alternative method was environmentally sustainable, and concentration and temperature had a significant impact on color and other factors. To utilize data mining and intelligent technology for high-quality product production, Saba et al. (2024) developed an intelligent operation guide to adjust the production process parameters of deformed yarn based on raw material specifications, to obtain high-quality products at low cost. The method involves a literature review and the identification of key factors using data mining techniques such as deep learning. Dynamic guidelines were developed using Power BI and applied to the production of a company in Iran from 2020 to 2021. The results showed that the influence of process parameters was more significant, forming a dynamic guide with an accuracy of about 80%, which can predict relevant indicators and is updated every three months. In view of the problem that it is difficult to accurately predict a single model of industrial time series due to multiple parameters and complex responses, a hybrid method, which takes spatiotemporal attention and a time convolution network as the basis, was proposed by Lu et al. (2024) to tackle the characteristics of multiple coupling and dynamic nonlinearity. The method was verified to be effective and accurate by two real data sets.

In summary, existing research on the clothing production process in the textile industry either focuses only on static modeling and cannot capture dynamic changes, or the prediction models ignore the correlation between various links in the production process, resulting in low prediction accuracy. Therefore, the study innovatively integrates knowledge graphs with graph spatiotemporal attention networks to construct a textile and clothing production process model and make predictions, aiming to solve practical problems in current textile and clothing production.

The innovation of this study is mainly reflected in, first, the deep integration of the knowledge graph and the graph spatiotemporal attention network. Knowledge graph represents the correlation between production factors through structured representation, solving the problem of "lack of industry knowledge guidance" in existing models. When capturing spatiotemporal features, the graph spatiotemporal attention network can use the entity weight and relationship strength information of the knowledge graph to prioritize core production factors and improve the pertinence of feature extraction. The second is the innovation of predictive ability. The model simultaneously considers spatial correlation and temporal dependence, and dynamically adjusts the weights of key nodes and key time periods through a spatiotemporal attention mechanism, which can adapt to two production scenarios: multi-variety small batch and large-scale standardization. The third is the innovation of application value. The model can not only predict the production process but also visualize the correlation of production factors through knowledge graphs, helping enterprises to intuitively identify bottleneck processes. At the same time, it provides a quantitative basis for optimizing production resource allocation through entity weight calculation, providing a new technological path for intelligent prediction of production processes in the textile industry, and laying the foundation for subsequent research on intelligent and policy-aligned manufacturing systems.

The structure of this article is as follows. The first section elaborates on the research background, significance, and prospects of the clothing production process. The second section focuses on the research and design of a clothing production prediction method, which is based on a knowledge graph and a graph spatiotemporal attention network. The third section elaborates on the experimental verification and analysis of experimental data results based on the algorithm designed in the second section. The fourth section draws conclusions about the experimental findings and elaborates on the deficiencies of this design and the directions that need to be further explored in the future.

2. Methods and Materials

The research proposes a method for predicting the production process in the textile and clothing industry, based on a knowledge graph and a graph spatiotemporal attention network. First, a knowledge graph-based model of the textile and clothing production process is constructed to clearly present the relationships between various production links. Then, a fused graph spatiotemporal attention network is used to analyze and predict the production process.

2.1. Construction of a Textile and Clothing Production Process Model Based on a Knowledge Graph

The manufacturing process within the textile and clothing industry encompasses several sequential links, such as raw material procurement, cutting, sewing, ironing, and packaging, with complex dependencies between them. The traditional process representation method struggles to clearly and comprehensively display these relationships, resulting in poor information transmission and difficulty in troubleshooting during the production process (Chang and Xu, 2024).

Knowledge graphs can effectively depict these complex associations by representing entities and relationships, providing a foundation for the management and optimization of production processes (Khadijeh et al., 2023). This research aims to define the entities and relationships in the textile and clothing production field, construct a knowledge graph, and achieve accurate modeling of the production process. The constructed knowledge graph provides the basic entity and relationship information for the fused graph spatiotemporal attention network to predict production processes. The graph spatiotemporal attention network can capture dynamic changes in production processes based on this information.

Knowledge graph technology can integrate dispersed production factors into a structured knowledge network through entity-relationship modeling. For example, the triplet of "pure cotton fabric-supply-cutting process" can intuitively present the material flow logic. The graph spatiotemporal attention network can further explore hidden dynamic patterns. Its spatial attention mechanism can focus on the strong correlation between "bottleneck equipment-key processes", and its temporal attention mechanism can capture the temporal dependence of "order fluctuations production capacity adjustments" (Zhao and Xiaohong, 2023). During the construction of the knowledge graph, the core entities of the textile industry's clothing production process were identified. Through interviews with domain experts and production data mining, five types of core entities and seven types of key relationships were identified, as shown in Fig. 1.

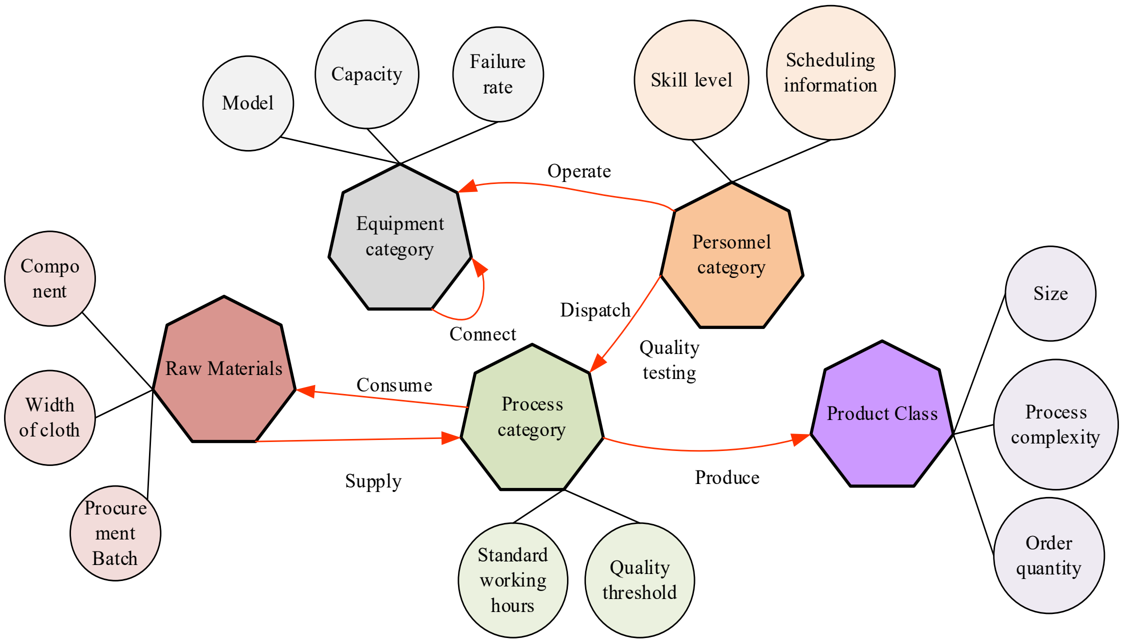


Fig. 1. Core entity relationship classification diagram for textile and clothing production

As shown in Fig. 1, the entity includes raw materials, equipment, processes, personnel, and products. Relationships cover types such as supply, operation, connection, quality inspection, and scheduling. The entity set E is defined in the production process, including raw material e_m, equipment e_d, process e_p, personnel e_r, etc., i.e. $E = \{e_m, e_d, e_p, e_r, \cdots\}$. The relationship set R between entities, such as raw material supply relationship r_s, equipment operation relationship r_o, process connection relationship r_c, etc. $R = \{r_s, r_o, r_c, \cdots\}$.

Taking Shandong Daiyin Textile and Clothing Group in Tai'an as an example, its production process integrating cotton spinning, weaving, and clothing processing provides a typical scenario for knowledge graph construction. In the enterprise's suit production process, the core entities include "combed cotton fabric" (raw material), "automatic laying machine" (equipment), "suit sleeve sewing process" (technology), "quality inspector Zhang" (personnel), and "finished suit" (product).The relationships between entities is clearly presented as follows: "combed cotton fabric flows through the supply relationship to the automatic cutting process", "the automatic laying machine is operated by cutting worker Mr. Li", "and the sleeve sewing process is connected to the finished product inspection process via a quality inspection relationship". By collecting the enterprise's production data from the past 3 years (such as fabric procurement records, equipment operation logs, and process handover orders), the above entities and relationships are quantified as triplets in the knowledge graph; for example, (combed cotton fabric, supply, automatic cutting process), (automatic laying machine, operation, Master Li).

The establishment of triplets within the knowledge graph employs a hybrid approach that combines top-down and bottom-up strategies, along with an ontology framework defined from top to bottom, as shown in Fig. 2.

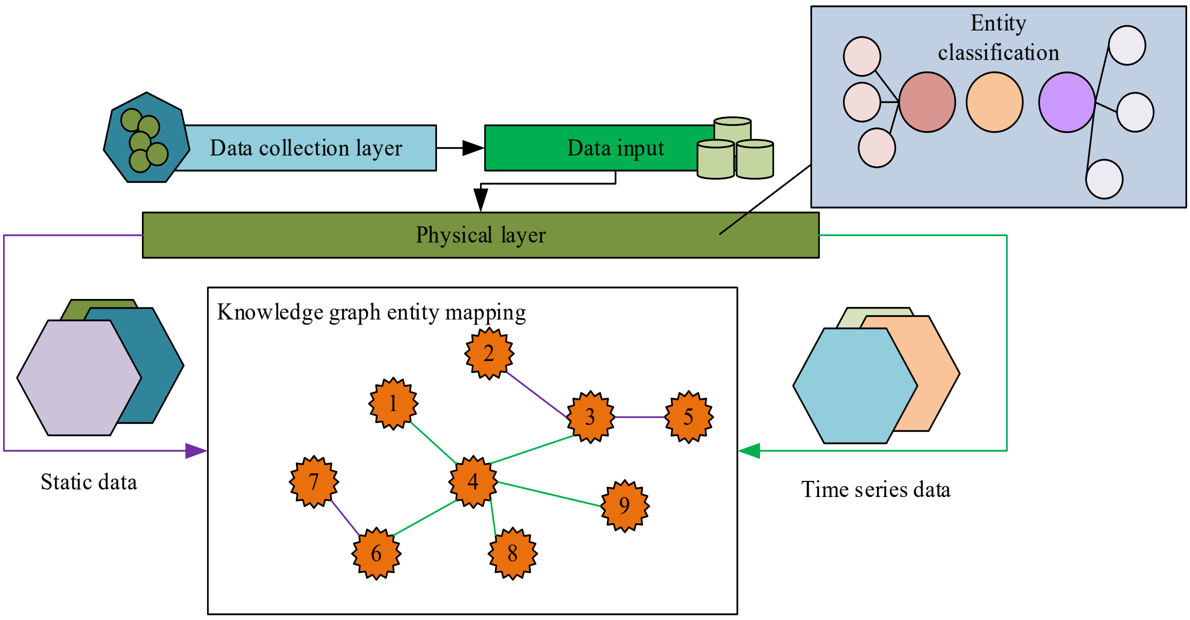


Fig. 2. The ontology framework diagram of the knowledge graph for textile and clothing production in the textile industry

As shown in Fig. 2, the data acquisition layer obtains static data such as fabric composition, equipment model and temporal data, including process time, equipment energy consumption changes. After input, the static and dynamic data flow into the entity layer. In the entity mapping process of the knowledge graph, nodes represent production entities (raw materials, equipment, processes, etc.), and edges form entity relationships. By integrating static attributes (inherent characteristics of entities) with dynamic temporal information (production data that changes over time), a knowledge network of production factors is constructed, providing a structured knowledge foundation for subsequent graph spatiotemporal network analysis of production processes and achieving the transformation of production data into an analyzable network.

To quantify the importance of entities, the study introduces entity weight calculation. The weight ω_i of entity e_i is calculated based on its degree d_i in the knowledge graph, as shown in Eq. (1).

$$\omega_i = \frac{d_i}{\sum_{k \in E} d_k} \tag{1}$$

In Eq. (1), d_i is the degree of entity e_i, which is the number of relationships k associated with that entity, and E is the set. For the strength of the relationship, a calculation method based on co-occurrence frequency is adopted. If the frequency of the relationship r appearing in the triplet is f_r, then the relationship strength s_r is shown in Eq. (2).

$$s_r = \frac{f_r}{\sum_{k \in R} f_k} \tag{2}$$

In Eq. (2), R represents a set. To expand and update the knowledge graph, entity similarity calculation is defined. The similarity $sim(e_i, e_j)$ is shown in Eq. (3).

$$sim(e_i, e_j) = \frac{v_i \cdot v_j}{\| v_i \| \cdot \| v_j \|} \tag{3}$$

In Eq. (3), $sim(e_i, e_j)$ is similarity, $v_i$and v_j are the cosine similarities of e_i and e_j attribute vectors, when the similarity is greater than the set threshold θ, it is considered that there is a potential association between the two entities, which can be used for expanding the knowledge graph. Based on the calculation results of Eqs. (1) - (3), a weighted knowledge graph is generated, taking the cutting and sewing process as an example, as shown in Fig. 3.

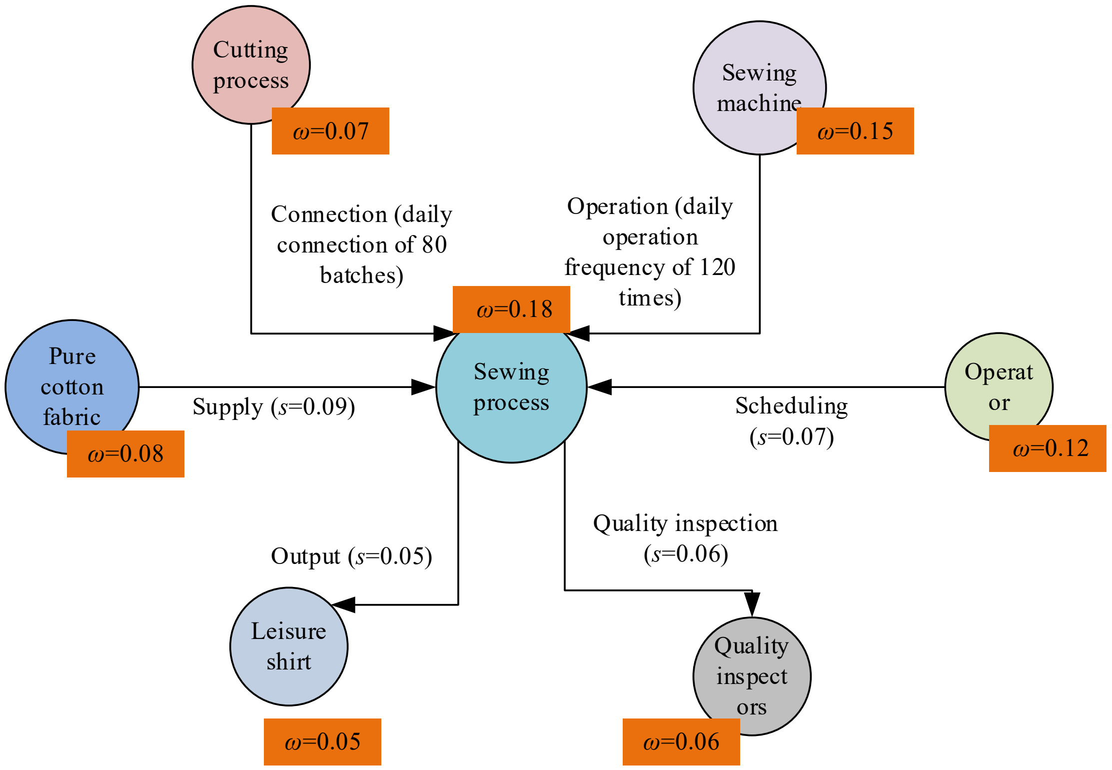


Fig. 3. Partial schematic diagram of weighted knowledge graph

As shown in Fig. 3, taking the sewing process of clothing production as an example, circular nodes are used to represent entities such as pure cotton fabric and cutting processes, and ω is used as the entity weight, calculated based on the number of correlation relationships. Arrows are used to display supply, connection, and other relationships, s is the strength calculated based on the frequency of the relationship, clearly presenting the correlation between production factors and core processes (sewing processes are highly correlated, with a critical value of $\omega = 0.18$), providing structured knowledge support for subsequent process analysis and prediction.

2.2. Prediction of Textile and Clothing Production Process Using Fusion Graph Spatiotemporal Attention Network

As an important base for the textile and clothing industry in Shandong Province, Tai'an is home to leading enterprises such as Shandong Daiyin Textile and Clothing Group and Shandong Ruyi Smart Textile and Clothing Co., Ltd. These enterprises generally face problems such as high waiting times for process connections and large fluctuations in equipment load when producing multiple varieties and small batch orders. The traditional production management model struggles to dynamically coordinate the chain reaction of "fabric supply, delay sewing process backlog, delivery delay", and there is an urgent need for accurate production process prediction and optimization methods. By constructing a knowledge graph, the study clearly presents the static relationships between various entities in the clothing production process, but it cannot reflect the dynamic changes and temporal correlations. The graph spatiotemporal attention network can simultaneously process graph structure information and time series information, making it suitable for predicting clothing production processes with complex correlations and dynamic changes (Wolthuis, 2024). Therefore, the study introduces graph spatiotemporal attention networks and integrates knowledge graph information for production process prediction. Converting a knowledge graph into the input format of a graph spatiotemporal network requires graph structure mapping, as shown in Fig. 4.

Fig. 4 presents the transformation process from a knowledge graph to a graph spatiotemporal network input. Starting from the input layer, the knowledge graph carries production-related information, which is then processed through entity extraction (screening core production factors), feature extraction (mining entity attributes and time-series data), and a mapping layer (fusion processing). Ultimately, this is converted into a graph network structure, achieving a transformation from static knowledge graph associations to dynamic network inputs and laying the foundation for subsequent analysis of production processes by the spatiotemporal attention network. This corresponds to the data preparation logic in the spatial feature extraction and temporal information capture stages of Eqs. (4)-(11).

Let the time series data be $X = \{x_1, x_2, \cdots, x_t\}$. Construct a graph structure by using entities in the knowledge graph as graph nodes, relationships as edges, edge sets corresponding to relationships between entities, and node sets corresponding to entities in the knowledge graph (Abd, 2025; Kim and Kim, 2024).

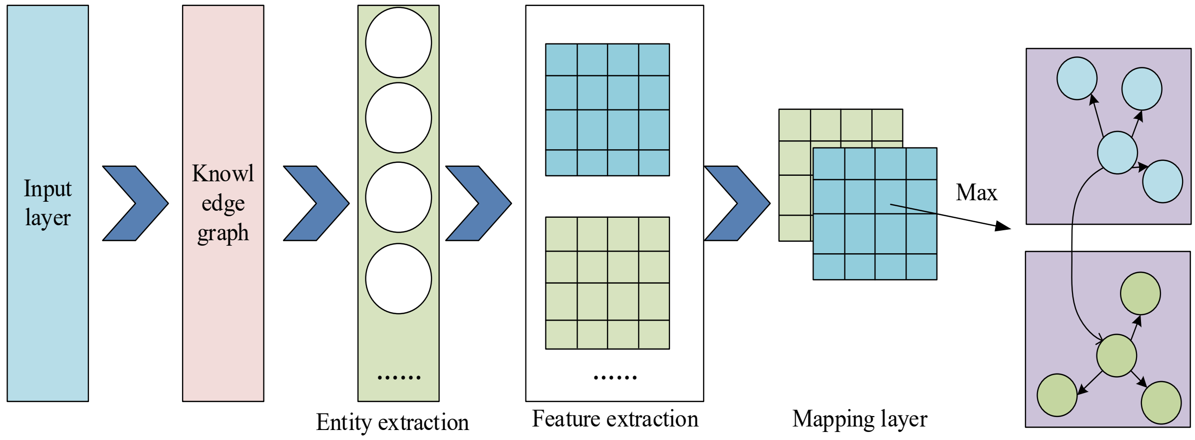


Fig. 4. Mapping relationship diagram from knowledge graph to graph network

The graph structure is embedded and represented using Graph Convolutional Networks (GCN) to extract spatial features. The output $H^{(l)}$ is shown in Eq. (4).

$$H^{(l)} = \sigma\left(\hat{A}H^{(l-1)}W^{(l)}\right) \tag{4}$$

In Eq. (4), $W^{(l)}$ denotes the weight matrix of the l-th layer, l represents which layer, $\widehat{D}$ denotes the degree matrix, A denotes the adjacency matrix, $\hat{I}$ denotes the identity matrix, $\hat{A} = \widehat{D}^{-\frac{1}{2}}(\hat{I} + A)\widehat{D}^{-\frac{1}{2}}$ denotes the normalized adjacency matrix, and σ denotes the activation function. To capture temporal information, a Gated Recurrent Unit (GRU) is introduced. The update gate z_t is shown in Eq. (5).

$$z_t = \sigma\left(W_z x_t + U_z h_{t-1}\right) \tag{5}$$

In Eq. (5), U_z means the weight matrix of the historical state, W_z means the weight matrix of the current time data, z_t represents the output of the update gate, x_t represents the current time input, and h_{t-1} means the historical hidden state. Door r_t is reset as shown in Eq. (6).

$$r_t = \sigma\left(W_r x_t + U_r h_{t-1}\right) \tag{6}$$

In Eq. (6), W_r means the weight matrix of the input x_t at the current time, and U_r means the weight matrix of the historical hidden state h_{t-1}. The candidate hidden state $\tilde{h}_t$ is shown in Eq. (7).

$$\tilde{h}_t = \tanh\left(W_h x_t + r_t \odot U_h h_{t-1}\right) \tag{7}$$

The final hidden state h_t is shown in Eq. (8).

$$h_t = (1 - z_t) \odot h_{t-1} + z_t \odot \tilde{h}_t \tag{8}$$

In Eqs. (7) - (8), $W_z, U_z, W_r, U_r, W_h, U_h$ indicate the weight matrices and $\odot$ is the element multiplication. The outputs of GCN and GRU are integrated and a spatiotemporal attention mechanism is introduced. The attention weight $\alpha_{t,k}$ for the time dimension is shown in Eq. (9).

$$\alpha_{t,k} = \frac{\exp\left(s(h_t, h_k)\right)}{\sum_{m=1}^{T} \exp\left(s(h_t, h_m)\right)} \tag{9}$$

In Eq. (9), $s(h_t, h_k\})$ is the similarity function between the hidden states h_t and h_k, which can be calculated using the inner product. The attention weight $\beta_{i,j}$ in spatial dimension is shown in Eq. (10).

$$\beta_{i,j} = \frac{\exp\left(q_i \cdot k_j\right)}{\sum_{n=1}^{N} \exp\left(q_i \cdot k_n\right)} \tag{10}$$

In Eq. (10), q_i and k_j are the query vectors of nodes i and j. The output y_t after fusing spatiotemporal attention weights is shown in Eq. (11).

$$y_t = \sum_{k=1}^{T} \alpha_{t,k} \sum_{j=1}^{N} \beta_{i,j} h_{k,j} \tag{11}$$

In Eq. (11), $\beta_{i,j}$ represents spatial attention weight, $\alpha_{t,k}$ represents temporal attention weight, and $h_{k,j}$ represents spatiotemporal fusion. The comprehensive architecture of the spatiotemporal attention network is illustrated in Fig. 5.

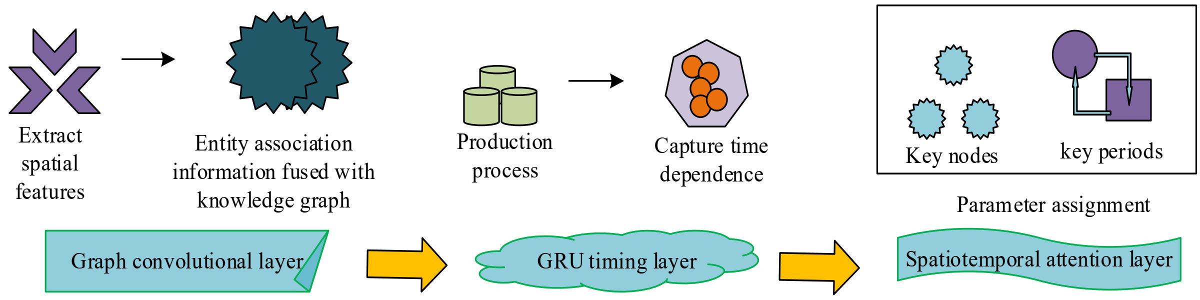


Fig. 5. The overall framework of graph spatiotemporal attention network

Fig. 5 illustrates the comprehensive architecture of the graph spatiotemporal attention network. It first obtains spatial attributes (such as links between production entities) using graph convolutional layer., and integrates entity association information from the knowledge graph. Production process data is processed by the GRU temporal layer to capture time dependencies (such as the sequence of processes). Finally, the spatiotemporal attention layer assigns weights to key nodes (such as bottleneck devices) and critical time periods (such as production peaks) to achieve deep mining of the spatiotemporal characteristics of the clothing production process, thereby supporting production process prediction.

To improve prediction accuracy, residual connections and layer normalization are introduced (Yu and Zhu, 2024). The formula for the residual connection is shown in Eq. (12).

$$H_{res} = H + F(H) \tag{12}$$

In Eq. (12), H is the input and $F(H)$ refers to the mapping function of the network. The layer normalization formula is shown in Eq. (13).

$$LN(H) = \gamma \cdot \frac{H - \mu}{\sqrt{\sigma^2 + \epsilon}} + \beta \tag{13}$$

In Eq. (13), μ is the mean, σ^2 is the variance, γ, β are the learnable parameters, and ϵ is the small value to prevent zero division. The final predicted value $\hat{y}_{t+1}$ is obtained through a fully connected layer, as denoted in Eq. (14).

$$\hat{y}_{t+1} = W_{out} y_t + b_{out} \tag{14}$$

In Eq. (14), W_{out} and b_{out} denote the weight values and bias coefficients corresponding to the fully connected layer. The loss function adopts mean square error as shown in Eq. (15).

$$L = \frac{1}{M} \sum_{t=1}^{M} (y_{t+1} - \hat{y}_{t+1})^2 \tag{15}$$

In Eq. (15), M denotes the number of samples, y_{t+1} denotes the true value, and $\hat{y}_{t+1}$ represents the predicted value (Preethi and Mamatha, 2023). Based on the above process, the prediction of the textile and clothing production process using knowledge graph and graph spatiotemporal attention network is shown in Fig. 6.

As shown in Fig. 6, the first step is to collect production data from textile enterprises and preprocess it to construct a knowledge graph containing 5 core entities and 7 key relationships. Formulas are used to calculate entity weights and relationship strengths, generating a weighted graph. This graph is then mapped to a graph network (with entities as nodes, relationships as edges, and node features including attributes and temporal data), and to build a graph spatiotemporal attention network that integrates graph convolutional layers (to extract spatial features), GRU temporal layers (to capture temporal dependencies), and spatiotemporal attention layers (to assign weights to key elements). After training with the training set and evaluation with the testing set, the analysis results provide decision support for production while also clarifying research limitations and future directions.

3. Results

To validate the proposed method for predicting methods based on a knowledge graph and graph spatiotemporal attention network, an experiment was conducted to validate it, analyze the corresponding design parameters and experimental data results, and verify the advantages and feasibility of the method.

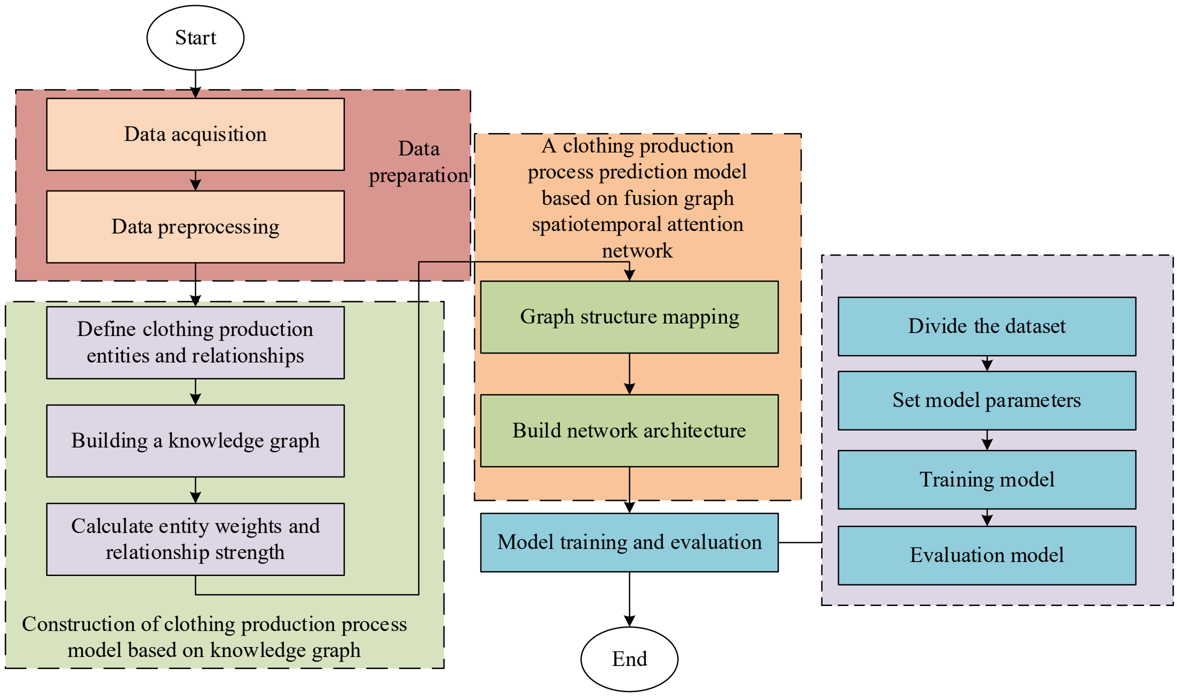


Fig. 6. Research process of textile and clothing production based on knowledge graph and graph spatiotemporal attention network

3.1. Experimental Preparation

The study used clothing production data from a large textile enterprise over the past three years as experimental data, including raw material procurement information, production time for each process, equipment operation status, and personnel operation records. The data was preprocessed to remove outliers and missing values, resulting in a set of 10,000 valid samples. In the experimental process, the data were partitioned into two parts: a training set and a testing set, with the two sets accounting for 70% and 30% of the total data, respectively. The model parameters were set as follows: The GCN had two layers, the GRU hidden layer dimension was 64, the learning rate was 0.001, the number of attention heads was 4, and the iterations were 100. The experimental environment and configuration are denoted in Table 1.

Table 1. Experimental environment and related parameters

Software environment	CPU: Intel Xeon E5-2698 v4 GPU: NVIDIA Tesla V100 (32GB), Memory: 128GB	Parameters	Knowledge Graph Parameters	500 entities, 800 relationships, weight calculation window (sliding window size=7 days)
	Framework: PyTorch 1.10.5, Programming Language: Python 4.0, Operating System: Ubuntu 19.20		GCN	Layer number=2, hidden dimension=64, activation function=ReLU, dropout=0.2
	Optimizer Adam, learning rate=0.001 (cosine annealing scheduling), batch size=32		GRU timing layer	Hidden dimension=64, time step=24 (based on hourly data), iteration count=100
	Mean square error (MSE)		Spatiotemporal attention layer	Attention heads=4, time attention window=12 hours, spatial attention neighborhood range=3 hop nodes

3.2. Knowledge Graph Model and Clothing Production Prediction Results

The experiment compared the fusion model with traditional time series prediction models, a GCN-only model, and a Space-time GCN (ST-GCN)-only model. The experiment used Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Coefficient of Determination (R^2) as evaluation metrics. The results are presented in Table 2. The proposed model outperformed other comparative models in various evaluation indicators, with RMSE, MAE, and R^2 of 3.28, 2.15, and 0.93, respectively, indicating that integrating knowledge graphs and graph spatiotemporal attention networks as a methodological framework can notably boost the prediction accuracy for the clothing production process.

Table 2. Prediction performance comparison among various models

Model	MAE	RMSE	R2
Traditional time series prediction model	5.23	7.89	0.72
GCN	4.12	6.35	0.79
ST-GCN	3.56	5.21	0.85
Research model	2.15	3.28	0.93

Fig. 7 presents the performance assessment outcomes from the comparative analysis of the research model. In Fig. 7(a), in the mean Average Precision (mAP) metric, the research model showed a continuous increase in average accuracy as iterations progressed and eventually approached 1.00, which was markedly better than those of the other comparative models. This reflects its advantages in capturing spatiotemporal correlations during production and boosting the precision of predictions. The research model injected industry knowledge through knowledge graphs and combined it with graph spatiotemporal attention networks to dynamically capture spatiotemporal features, ultimately achieving mAP breakthrough of 0.95 and accurately matching process collaboration requirements in multi-variety production. Traditional time series models relied solely on the historical time consumption of a single process, resulting in an accuracy of less than 0.3 in the first 20 iterations. GCN could mine process associations but lacked temporal dependency modeling, and its accuracy tended to plateau after improving to 0.7; ST-GCN (green line) added time convolution, and after 30 iterations, its accuracy was surpassed by the research model due to the constraint of not incorporating a knowledge graph. In Fig. 7(b), in the MAE metric, the average error of the research model rapidly decreased and remained low after iteration, while the errors of other models either decreased slowly (such as traditional time series models) or rebound later (such as ST-GCN). The research model maintained a stable MAE within 0.15. The traditional model always had an error higher than 0.3 due to neglecting the nonlinear correlation between equipment load and fabric tension. Although ST-GCN could capture spatiotemporal features, it did not utilize knowledge graphs and experienced an error rebound after 20 iterations. The research model, which integrates a knowledge graph and a spatiotemporal attention network, could learn the production process rules of textiles and clothing more efficiently, accurately reduce prediction errors in iterative optimization, and provide more reliable support for production decision-making. This verifies the effectiveness and superiority of the method in improving production prediction performance.

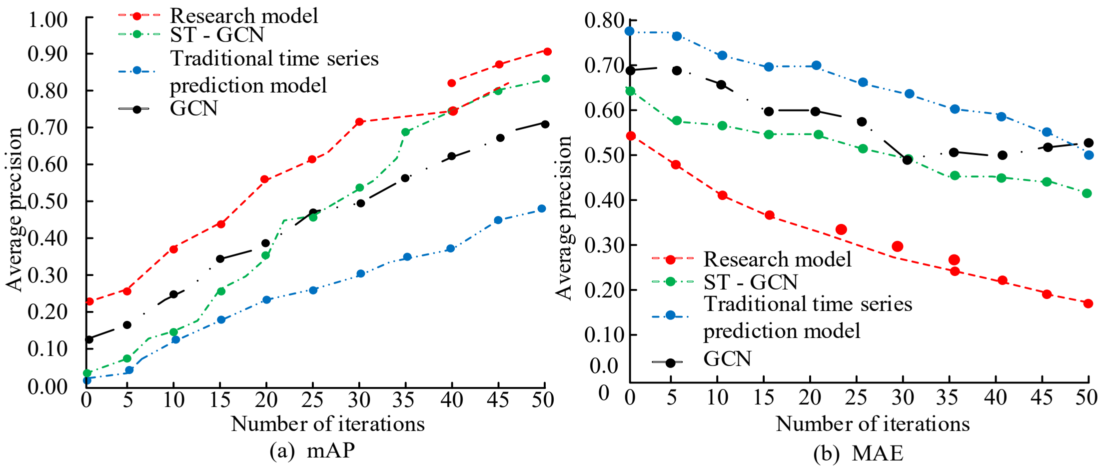
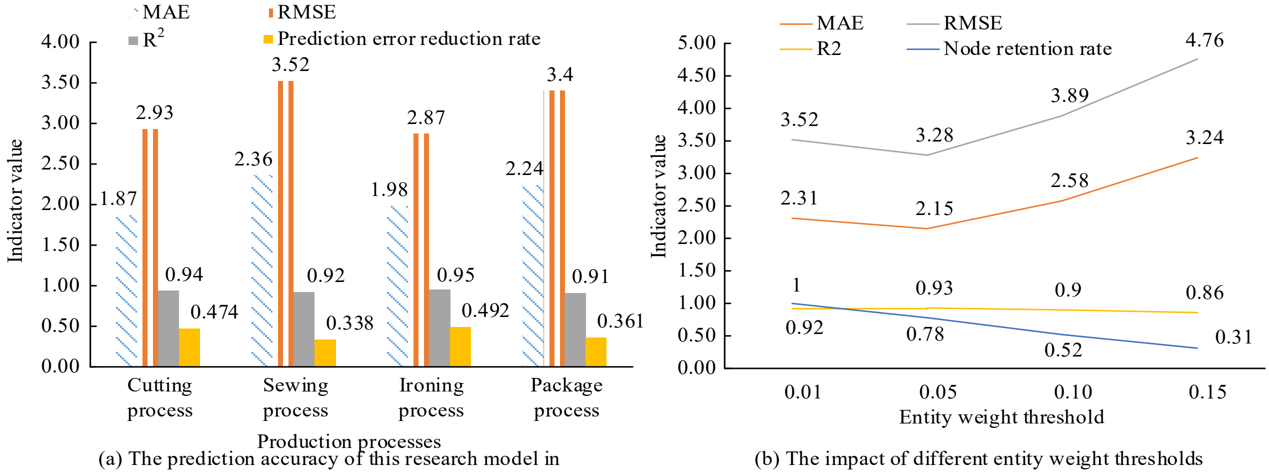


Fig. 7. Comparison of precision in clothing production analysis of different models

Fig. 8 shows the prediction precision of the research model at different production stages and the impact of different entity weight thresholds on model performance. The prediction error rate was relative to the ST-GCN model. In Fig. 8(a), the MAE was between 1.87 and 2.36, the RMSE was between 2.87 and 3.52, and the R^2 was between 0.91 and 0.95, reflecting the high accuracy of the model's predictions for each link. Compared with ST-GCN, the prediction error reduction rate was 33.8%-49.2%, indicating that the model that integrates knowledge graph and graph spatiotemporal attention network can successfully seize the spatiotemporal correlations in the production process. Due to strong process dependence and equipment correlation in cutting, ironing, and other processes, the error reduction was more significant. The validation method is suitable for textile production processes and helps with precise scheduling and quality control. In Fig. 8(b), when the threshold was 0.01, the node retention rate was 1 (retaining all entities), but due to redundant information, the MAE was 2.31 and RMSE was 3.52. When the threshold was 0.05, 78% of key entities were retained. The model focused on core correlations, the MAE dropped to 2.15, and the R^2 reached 0.93, indicating optimal performance; When the threshold was 0.1 and 0.15, the node retention rate was too low (52%, 31%, respectively), and the loss of key associations led to a surge in error (MAE increased from 2.58 to 3.24). It can be seen that setting a threshold of 0.05 can balance entity information and model efficiency. The knowledge graph needs to screen core production associations to provide an optimization basis for the accuracy and practicality of textile production prediction models.

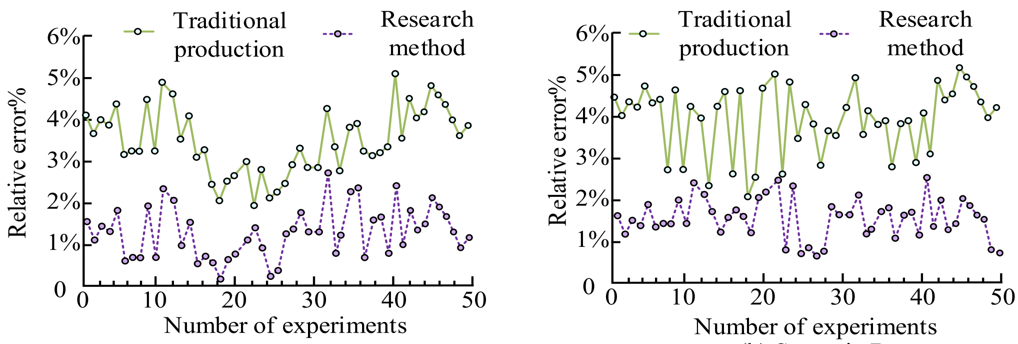


(a) The prediction accuracy of this research model in different production stages

(b) The impact of different entity weight thresholds on model performance

Fig. 8. How the research model performs prediction accuracy at different production stages, and the effect of weight thresholds on the model's operational performance

Fig. 9 shows the relative error performance of the research method and traditional production modes in two clothing production scenarios. Scenario A involves multi-variety small batch production (customized orders account for 60%), while Scenario B involves large-scale standardized production (basic orders account for 85%). In both Scenario A and B, the purple dashed line representing the research method was consistently within the lower relative error range, while the green solid line representing the traditional production mode showed greater fluctuation and higher errors. In Scenario A, the traditional mode error often exceeded 3%, while the research method was within 2%. In Scenario B, the traditional mode error frequently surged, whereas the research method was more stable. This indicates that the model integrating a knowledge graph and a graph spatiotemporal attention network can effectively capture the spatiotemporal correlations of production processes, accurately predict process fluctuations, and significantly reduce production errors. The research method demonstrates better stability and accuracy than traditional models across different production scenarios, verifying its applicability and reliability in complex production environments, and providing strong technical support for optimizing textile and clothing production.



(a) Scenario A

(b) Scenario B

Fig. 9. The relative error performance of research methods and traditional production modes in two clothing production scenarios

Fig. 10 shows the task distribution of different machine groups (Machine groups 10-18) in the time dimension of textile and clothing production. It can be seen that Machine Group 12 undertook bottleneck processes, with long task times and wide coverage (approximately 0-500 time periods), reflecting its tendency to be congested in the production process; Machine group 14 executed the pre-process, with continuous task distribution and connection to the bottleneck processes. By arranging tasks on the timeline, one can visually observe the time periods and loads in which each machine group participates in production, helping to identify key processes (such as the bottleneck process in Group 12) and task connection issues across production stages. This serves as a visual foundation for improving the efficiency of equipment scheduling and alleviating bottlenecks, and it verifies the ability of knowledge graphs and graph spatiotemporal networks to capture production process characteristics.

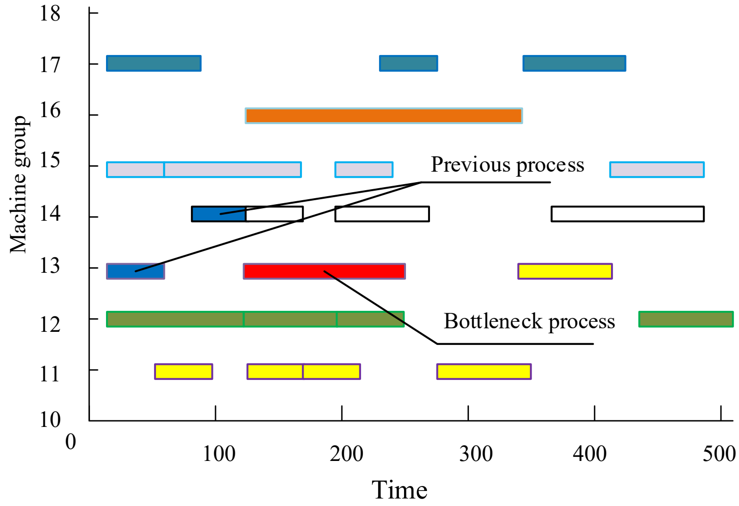


Fig. 10. The task distribution of different machine groups (machine group 10-18) in the time dimension of textile and garment production

The research proposes a textile and clothing production process model based on a knowledge graph and graph spatiotemporal attention network, which aligns closely with multiple policy directions at the current national and industry levels. In terms of intelligent manufacturing policies, the model can effectively reduce production energy consumption by accurately predicting the production process and optimizing equipment scheduling. According to experimental data, the application of the model increased equipment utilization by approximately 15%-20%, indirectly reducing energy waste caused by equipment idling, which meets the requirements of "promoting the green and low-carbon transformation of the manufacturing industry" in the "14th Five-Year Plan" for the development of intelligent manufacturing. At the policy level of digital transformation in the textile industry, the model transforms dispersed production data into a structured knowledge network, achieving digital management of production factors and responding to the policy call to "accelerating the digital, networked, and intelligent transformation of the textile industry" in the "Guiding Opinions on Promoting High-Quality Development of the Textile Industry". In addition, the model's accurate prediction capability for multi variety and small batch production helps to improve the level of flexible production of enterprises, aligning with the national productivity strategy to "supporting personalized customization and flexible production in the manufacturing industry", and providing technical support for the textile industry to implement national policies.

For textile enterprise managers, the model application can follow these implementation steps: firstly, in the data preparation stage, integrate the production data of the enterprise in the past 3-5 years, and assign dedicated personnel to clean and standardize the data to ensure data quality; In the second step, during the knowledge graph construction phase, a specialized team of "technical personnel and industry experts" can be formed to refine the definition of entities and relationships based on the actual production process of the enterprise. At the same time, training can be provided to enable the team to master the calculation methods of entity weights and relationship strength; The third step, model deployment phase, prioritizes pilot applications in bottleneck production processes of enterprises, compares the model's prediction results with actual production data, gradually optimize model parameters, and fully promotes it after the pilot effect is significant. For government regulatory departments, industry-level application guidelines can be developed based on this model. First, the core indicators of the model can be incorporated into an intelligent manufacturing evaluation system of the textile industry to guide enterprises to improve the level of intelligent production processes; Second, organize model application training and collaborate with universities and research institutions to provide technical guidance to local textile enterprises, especially for small and medium-sized enterprises, can reduce the deployment cost of enterprise models through government subsidies and promote the overall production efficiency of the industry.

There are three core obstacles to the actual promotion of the model: firstly, the high infrastructure costs, which requires high-performance computing equipment for model operation, which is difficult for small and medium-sized enterprises to afford. The "cloud deployment" model can be adopted, where the government collaborates with third-party technology enterprises to build an industry level cloud computing platform, and with enterprises paying as needed to reduce initial investment; Secondly, insufficient digital literacy of personnel, and enterprise employees have limited understanding of technologies such as knowledge graphs and graph neural networks, making model operation difficult. Layered training can be conducted through "school enterprise cooperation", focusing on data collection and result interpretation for grassroots personnel, parameter adjustment and maintenance training for technical personnel, and supported by user-friendly operation manuals; Thirdly, data integration is difficult. Some enterprises have "data islands", and production data is scattered in different departmental systems, making uniform data retrieval difficult. It is recommended that the government promote the development of industry data standards, clarify interface specifications, encourage enterprises to use industrial Internet platforms to achieve data interconnection, and lay a solid data foundation for model application.

4. Conclusion

The study innovatively combined a knowledge graph with graph spatiotemporal attention network to construct a production process model for the textile and clothing industry, and conducted research on production process prediction. The findings indicated that the model proposed in this study showed better performance than other reference models in a variety of evaluation indicators, with RMSE, MAE, and R^2 values of 3.28, 2.15, and 0.93, respectively. This indicates that the method of integrating knowledge graphs and graph spatiotemporal attention networks can significantly improve the accuracy of predictions for the clothing production process. The research model maintained a stable MAE control within 0.15. Whether in Scenario A or B, the purple dashed line representing the research method remained consistently in a lower relative error range, while the green solid line of the traditional production mode fluctuated greatly and had high errors. In Scenario A, the traditional mode error often exceeded 3%, while the research method was within 2%. In Scenario B, the traditional mode error frequently surged, and the research method was more stable. When the threshold was 0.01, the node retention rate was 1, but due to redundant information (MAE 2.31 and RMSE 3.52), when the threshold was 0.05, 78% of key entities were retained. The model focused on core correlations, the MAE dropped to 2.15, and the R^2 reached 0.93, indicating optimal performance; When the threshold was increased to 0.1 and 0.15, the node retention rate was too low (52%, and 31%, respectively), and the loss of key associations led to a surge in error (MAE increased from 2.58 to 3.24). In summary, the model proposed in this study has superior prediction accuracy to conventional models and can provide effective decision support for the textile and clothing production industry. However, there are also some limitations to the research, such as the fact that the experimental data only came from one company, which may have specific constraints. Looking forward, expanding the data sources will help improve the model's generalizability. Meanwhile, the construction of knowledge graphs still relies on the manual delineation of entities and their relationships, which may contain omissions. Further research can be conducted on methods for automatically constructing knowledge graphs.

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Author Contributions

Rubin Hou contributes to conceptualization, analysis, data collection, and manuscript editing. Yan Ma contributes to methodology, software, validation, and manuscript editing. All authors have read and agreed with the manuscript before its submission and publication.

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Declaration of Artificial Intelligence (AI) Tools

The authors confirmed that no AI tools were used in the preparation of this manuscript.

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