

Augmented reality-based intelligent manufacturing system for clothing customization: user immersive interaction and process visualization method

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Abstract

INTRODUCTION: AR-based clothing customization improves user interaction, but multimodal customer requirements remain weakly connected to process planning and shop-floor scheduling.

OBJECTIVES: This study develops a closed-loop method that converts immersive interaction data into executable manufacturing decisions.

METHODS: A KG-DT-MARL framework was developed to encode body scans, speech, gestures, touch inputs, and fabric preferences into a six-element semantic graph, synchronize order, equipment, material, process, and quality states through a digital twin, and perform constraint-guided multi-agent scheduling.

RESULTS: The framework achieved 96.38% requirement-parsing accuracy, 95.74% process-chain generation accuracy, 91.86% resource utilization, and 94.62% on-time delivery under the tested order and disturbance scenarios.

CONCLUSION: The framework provides a closed-loop connection between immersive customization and visualized manufacturing execution.

Keywords: Clothing customization; Intelligent manufacturing; Process visualization; Knowledge graph; Digital twin

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1. Introduction

Custom-made clothing manufacturing is moving from traditional tailoring and standardized order production to personalization, flexibility and intelligence. As consumers' demands for style fit, wearing experience, fabric selection and delivery cycle continue to rise, relying solely on manual communication, static style display and offline process design is no longer sufficient to meet diverse customization needs [1-2]. Augmented Reality (AR) interaction, semantic modeling, and manufacturing digitalization provide technical support for clothing customization. However, the connection between user-side immersive interaction and manufacturing execution remains limited by incomplete

data conversion, delayed process response, and insufficient resource coordination [3-4]. Yu et al. proposed a digital human body modeling method based on 3D body scanning and linear regression to improve the accuracy of human body fitting in intelligent clothing customization. The research results show that this method can extract key body shape features and provide reliable parameter support for personalized pattern making and virtual fitting [5]. Shi et al. proposed a technical framework that integrates human body modeling, clothing structure modeling and virtual display to improve personalized expression and virtual display effect in intelligent customization of ethnic clothing. The findings

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suggest that the approach contributes to enhancing the visualization, interactivity and design fit of clothing customization [6].

AR technology can integrate body scanning, voice input, gesture selection and virtual try-on into interactive scenarios, providing an intuitive entry point for users to express their needs [7]. Cui et al. proposed an interactive design approach that combines additive manufacturing and AR to enhance remote collaboration and creative expression in the early design stage. The findings suggest that the approach can enhance the spatial perception and remote collaboration efficiency of design schemes [8]. However, if these interaction data cannot be transformed into executable parameters at the manufacturing end, it will still be difficult to support intelligent collaboration in subsequent cutting, sewing, ironing and quality inspection processes. Knowledge Graph (KG) can organize semantic relationships among users, human bodies, clothing, fabrics, processes, and resources, transforming natural interaction requirements into inferential structured knowledge [9]. Xiao et al. proposed a KG technology review framework for manufacturing process planning to enhance knowledge organization and reasoning capabilities in manufacturing process planning. The research results show that KG can effectively support process knowledge representation, extraction, construction, verification and process generation [10]. Multi-Agent Reinforcement Learning (MARL) can model orders, processes, resources, quality, and feedback as multiple collaborative decision-making agents for dynamic scheduling and anomalous response. Kaven et al. proposed an MARL method to optimize online layout planning and production scheduling in flexible assembly systems. The research results show that this method can achieve multi-agent collaborative decision-making in complex manufacturing scenarios and improve layout and scheduling optimization capabilities [11].

However, existing research has mostly focused on clothing personalization modeling, virtual display, or a single intelligent optimization link, and still lacks a closed-loop clothing customization intelligent manufacturing method that integrates AR interaction, knowledge semantic reasoning, Digital Twin (DT) state mapping, and multi-agent collaborative scheduling. Recent studies have investigated the deployment of KGs in smart manufacturing for heterogeneous data integration, semantic representation, and manufacturing knowledge reasoning. However, existing KG-based manufacturing solutions mainly focus on knowledge organization and information retrieval, while the coupling between KG reasoning and real-time production decision-making remains insufficient. DT can synchronously map the status of orders, equipment, workstations, materials and quality in a virtual space, providing real-time basis for manufacturing process monitoring and process adjustment [12]. Therefore, the research proposes a smart manufacturing method for clothing customization based on KG-DT-MARL, aiming to achieve an efficient transformation from user immersive interaction requirements to process visualization execution and collaborative optimization of manufacturing resources.

The methodological contribution lies in a garment-specific closed-loop coupling mechanism rather than in a new standalone KG, DT, or MARL algorithm. It converts multimodal AR interactions into a six-element production semantic graph and combines KG-derived manufacturability constraints with DT-synchronized workshop states to guide multi-agent scheduling and feed execution exceptions back to the requirement and process models.

2. Methods and materials

2.1. A method for parsing clothing customization requirements based on KG interactive semantic modeling

Existing clothing customization systems are capable of style selection, human body volume, and order recording, but voice description, gesture selection, virtual try-on feedback, and style preference in AR environments remain mainly at the interactive interface level and are difficult to be directly transformed into executable data at the manufacturing end [13]. Therefore, a KG-based interactive semantic modeling method is developed to convert immersive interaction data into structured customization semantics. A six-element knowledge network is then constructed for process reasoning and resource matching. Multimodal interaction data is the basis for analyzing clothing customization requirements. The system collects human body images, pose sequences, voice-text, gesture trajectories, and touch events via cameras, depth sensors, or mobile terminals. Let the user interaction features be denoted by x , comprising visual features x_v , speech features x_s , gesture features x_g , and style selection features x_c ; then, the multimodal fusion is represented as shown in Equation (1).

$$F = \phi(W_v x_v + W_s x_s + W_g x_g + W_c x_c + b) \quad (1)$$

In Equation (1), F represents the fused features of user-customized requirements; W_v , W_s , W_g , and W_c are the mapping weights for visual, speech, gesture, and style-selection features, respectively; b denotes the bias term; and ϕ represents the non-linear activation function [14]. Before fusion, all modality streams are timestamped and aligned within the same interaction-event window. Visual and gesture sequences are resampled to a unified length, while speech, touch, and style-selection events are assigned to the nearest time window. Each modality is processed by an independent encoder and projected into a common feature space before the weighted late fusion defined in Equation (1). Missing modalities are represented by zero vectors and therefore do not contribute to the fused feature. For noisy inputs, samples below the confidence threshold are removed, while the remaining features are weighted by their normalized confidence scores before fusion. Feature

normalization and dropout are further applied to reduce noise interference and prevent a single modality from dominating the representation. Following the fusion of interaction features, the user's natural requirements must be translated into parameters recognizable by the manufacturing system. Let d be the user requirement vector, h the human body parameter vector, p the garment component parameters, m the fabric property parameters, and c the manufacturing constraint parameters; the unified customization semantic vector is then represented as shown in Equation (2).

$$z = \text{Concat}(d, h, p, m, c) \quad (2)$$

In Equation (2), z is the custom semantic vector; Concat represents vector concatenation operations. This study constructs the data acquisition and semantic coding process for clothing customization interaction, as shown in Figure 1.

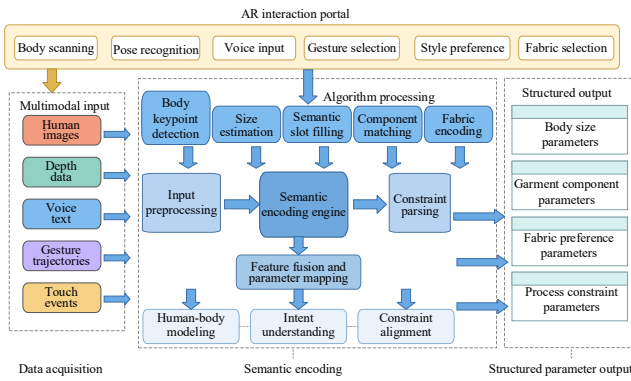


Figure 1. Multimodal AR interaction data acquisition and semantic encoding workflow, including body scanning, speech, gesture, touch, fabric selection, feature extraction, and structured parameter output

Figure 1 unfolds from the AR interaction entry point, demonstrating the data collection process including human body scanning, pose recognition, voice input, gesture selection, style preference, and fabric selection. On the left are multimodal inputs such as human body images, depth data, voice-text, gesture trajectories, and touch events. The middle part is processed by algorithms through human keypoint detection, size estimation, semantic slot filling, component matching, and fabric coding. The right side outputs structured parameters such as body size, garment parts, fabric preferences, and process constraints. The figure shows that AR interactions can transform users' natural behaviors into computable custom demand data through multimodal fusion and semantic encoding.

Interactive semantic coding can only parameterize requirements, and a more complete semantic association network needs to be established in combination with process rules, fabric attributes, and manufacturing resources. Let the entity set be E and the relation set be R , then clothing customization KG is represented as shown in Equation (3).

$$G = \{(e_i, r_k, e_j) \mid e_i, e_j \in E, r_k \in R\} \quad (3)$$

In Equation (3), G represents the clothing customization KG; e_i and e_j denote the head entity and tail entity, respectively; and r_k represents the semantic relationship between the entities [15]. To reduce redundant entities and semantic conflicts, the similarity calculation for entity fusion is defined as shown in Equation (4).

$$S(e_i, e_j) = \alpha S_c(e_i, e_j) + \beta S_s(e_i, e_j) + \gamma S_r(e_i, e_j) \quad (4)$$

In Equation (4), $S(e_i, e_j)$ is the comprehensive similarity; S_c represents name similarity, S_s represents semantic embedding similarity, and S_r represents relational neighborhood similarity; α , β , and γ are weighting coefficients. These coefficients are selected by grid search on the validation set with a step size of 0.05 under the constraint $\alpha + \beta + \gamma = 1$. The combination (0.30, 0.45, 0.25), which achieves the highest entity-fusion F1-score, is used in all experiments. A sensitivity analysis is further conducted by varying α , β , and γ within the feasible range while maintaining the constraint $\alpha + \beta + \gamma = 1$. The entity-fusion F1-score remains stable under moderate coefficient variations, indicating that the semantic fusion performance is not highly sensitive to individual coefficient selection.

When $S(e_i, e_j)$ exceeds a threshold, the system completes entity alignment or fusion. To illustrate the fusion relationship between the six-tuple ontology and multi-source data, a multi-source semantic knowledge fusion model for custom apparel is constructed, as shown in Figure 2.

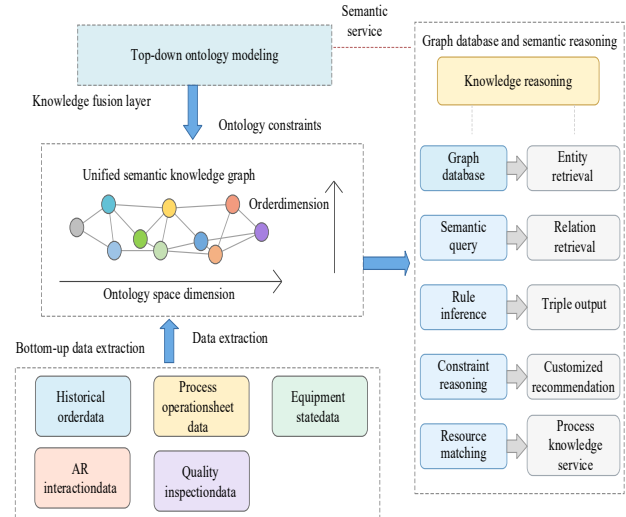


Figure 2. Multi-source semantic knowledge fusion model for clothing customization, showing the six-element ontology, heterogeneous data sources, entity alignment, conflict resolution, graph storage, and semantic reasoning

Figure 2 uses an up-and-down fusion structure, with the upper part being a top-down ontology modeling layer that includes six core ontologies: user, human body, clothing, fabric, process, and resource. The lower part is a bottom-up data extraction layer, including AR interaction data, historical order data, process operation order data, equipment status data, and quality inspection data. In the middle is the knowledge fusion layer, which includes entity extraction, relationship identification, entity alignment, conflict resolution, and triplet generation. On the right is the graph database and semantic inference module. The graph highlights KG's semantic organization ability for custom requirements, forming a unified interpretable network of user preferences, body size, garment structure, fabric attributes, process rules, and production resources.

2.2. Collaborative optimization of process visualization based on DT and MARL

The study completed semantic associations among user customization requirements, human body parameters, clothing components, fabric attributes, process rules, and manufacturing resources through KG interactive semantic modeling, enabling AR interaction results to be transformed into structured knowledge. However, the intelligent manufacturing of clothing customization still needs to solve the problems of how customization knowledge enters the production system, how an executable process chain is generated, and how resources are dynamically adjusted according to the workshop status [16]. Therefore, research is being conducted to construct a collaborative optimization method for process visualization that integrates DT and MARL, aiming to achieve manufacturing process mapping, process chain generation, resource scheduling, and on-site feedback updates. Let the physical workshop state be $P(t)$ and the DT state be $D(t)$. The specific calculation of the state synchronization error is shown in Equation (5).

$$\varepsilon(t) = \|P(t) - D(t)\|_2 \quad (5)$$

In Equation (5), $\varepsilon(t)$ represents the state deviation between the physical workshop and the DT model at time t ; $P(t)$ encompasses equipment status, workstation load, process progress, and quality inspection data; and $D(t)$ denotes the corresponding virtual mapping state. Minimizing $\varepsilon(t)$ ensures that the DT environment accurately reflects workshop operations, providing reliable state inputs for process optimization. Once a customized plan enters the manufacturing stage, the system performs garment-related searches based on the KG to generate a directed process task graph. When user requirements change, the system can update specific process nodes within the KG, thereby reducing the cost of reconstructing the entire production plan. To illustrate the data synchronization between the physical workshop and the virtual model, a DT-driven mapping model of the garment manufacturing process is constructed, as shown in Figure 3.

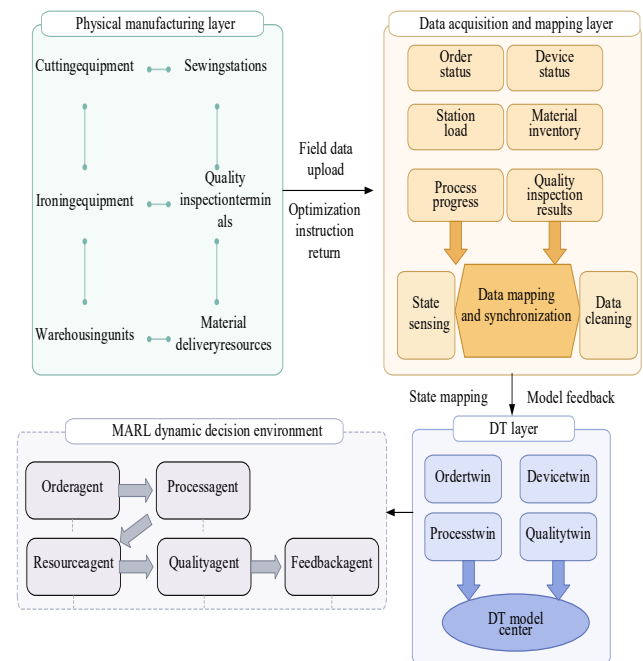


Figure 3. DT-driven clothing manufacturing process mapping model, showing physical resources, workshop data acquisition, virtual twin construction, state synchronization, and optimization instruction feedback

Figure 3 focuses on the virtual-real mapping relationship of the garment manufacturing process. The physical manufacturing layer includes cutting equipment, sewing stations, ironing equipment, quality inspection terminals, storage units, and material distribution resources. The data collection and mapping layer is responsible for aggregating order status, equipment status, workstation load, material inventory, process progress and quality inspection results. The DT layer creates order twins, equipment twins, process twins, quality twins, and logistics twins. On-site data are uploaded to the DT model, while optimization instructions are returned to the physical workshop. This bidirectional synchronization enables real-time state perception and model updating and provides dynamic state inputs for MARL. After the DT environment is established, dynamic decisions need to be made based on the production status. MARL is suitable for handling multi-agent collaborative optimization problems, modeling orders, processes, resources, quality, and field feedback as different agents respectively. The KG is initialized from AR interaction records, historical orders, garment component specifications, fabric attributes, process documents, equipment capability tables, and quality-inspection records. Entities and relations are first extracted automatically and then verified by process engineers before storage. New order, equipment, and quality data are incrementally added, while obsolete relations are retained with version identifiers for traceability. The DT receives equipment, workstation, material, process, and quality states at 1 s intervals. When

data are delayed or temporarily unavailable, the latest valid state is retained and marked with a timestamp and confidence value until synchronization is restored. Let the i th agent select action $a_{i,t}$ in state s_t and receive reward $r_{i,t}$; then, the update of the action value is calculated as shown in Equation (6).

$$Q_i(s_t, a_{i,t}) \leftarrow Q_i(s_t, a_{i,t}) + \eta [r_{i,t} + \lambda \max_{a_i} Q_i(s_{t+1}, a_i) - Q_i(s_t, a_{i,t})] \quad (6)$$

In Equation (6), Q_i is the action value function of the i th agent; η is the learning rate; λ denotes the discount factor; s_t means the current state; s_{t+1} is the next state [17-18]. To jointly consider resource utilization, delivery efficiency, manufacturing cost, quality risk, and user satisfaction, the comprehensive reward function is defined as shown in Equation (7).

$$R_t = \omega_1 U(t) - \omega_2 T(t) - \omega_3 C(t) - \omega_4 Q_d(t) + \omega_5 M(t) \quad (7)$$

In Equation (7), R_t is the comprehensive reward at time t ; $U(t)$ is resource utilization; $T(t)$ is the normalized delivery-time penalty, jointly calculated from process waiting time and order tardiness; $C(t)$ refers to manufacturing costs; $Q_d(t)$ stands for quality deviation or rework risk; $M(t)$ is user satisfaction; $\omega_1 \sim \omega_5$ are the weighting coefficients. All reward terms are normalized

before training. The weights $\omega_1 \sim \omega_5$ are determined through validation-set grid search and set to 0.25, 0.20, 0.15, 0.20, and 0.20, respectively, to balance resource utilization, waiting time, manufacturing cost, quality risk, and user satisfaction. To evaluate parameter robustness, each reward weight is perturbed by $\pm 10\%$, while the remaining weights are proportionally renormalized. The corresponding changes in average completion time, on-time delivery rate, and rework rate are evaluated over five random seeds. The sensitivity of the reward configuration is evaluated by perturbing each weight within $\pm 10\%$ while proportionally adjusting the remaining weights to preserve normalization. The variations in completion time, resource utilization, on-time delivery rate, and rework rate remains within a limited range, demonstrating the robustness of the reward design. The reward function enables the system to take into account manufacturing efficiency, quality stability and user experience during scheduling [19-20]. To further clarify the interaction mechanism between the KG, DT, and MARL modules, the overall decision-making procedure of the proposed KG-DT-MARL framework is summarized in Algorithm 1. The pseudocode describes the process of KG-based constraint extraction, valid-action filtering, DT state updating, multi-agent policy decision, and scheduling execution.

Algorithm 1. KG-DT-MARL decision procedure

Input: KG, DT state Sdt, MARL policies π , order set O

Output: Scheduling action A

- 1: Initialize current DT state Sdt
- 2: For each decision step t do
- 3: Obtain workshop state from DT
- 4: Query KG for:
 - process constraints,
 - resource availability,
 - equipment capability,
 - material compatibility
- 5: Generate valid-action mask M
- 6: Remove infeasible actions according to M
- 7: Extract KG embeddings of feasible entities
- 8: Combine DT state and KG embeddings
- 9: Each agent selects action using policy π
- 10: Calculate reward among feasible actions
- 11: Execute selected action in DT environment
- 12: Update DT state and repeat
- 13: End For

To demonstrate how MARL can achieve process generation and resource optimization in the DT environment, a DT-MARL process chain generation and resource co-optimization process is constructed, as shown in Figure 4.

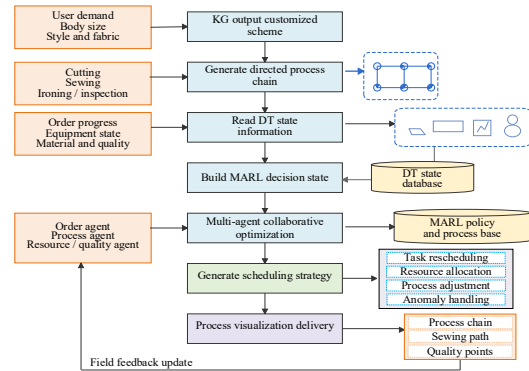


Figure 4. DT-MARL process-chain generation and resource collaborative optimization workflow, including KG-based process generation, DT state input, multi-agent decision-making, and scheduling strategy output

Figure 4 takes the custom scheme of KG output as input and first generates directed process chains such as cutting, sewing, ironing, quality inspection, etc. The DT environment then provides status information such as order progress, equipment availability, workstation load, material status, and quality risk. In the middle, order agents, process agents, resource agents, quality agents, and feedback agents are set up to complete order priority identification, process route selection, equipment and personnel matching, quality risk prediction, and on-site anomaly feedback respectively. The output includes task rescheduling, resource allocation, process adjustment, and anomaly handling strategies. The

scheduling strategy generated by DT-MARL still needs to be delivered to the workshop site through the process visualization module, allowing production personnel to have intuitive access to process chains, sewing paths, assembly sequences, dimensional tolerances, and quality inspection requirements. To further integrate KG semantic modeling, DT process mapping, and MARL collaborative optimization, the overall framework of the KG-DT-MARL intelligent manufacturing system for clothing customization is constructed, as shown in Figure 5.

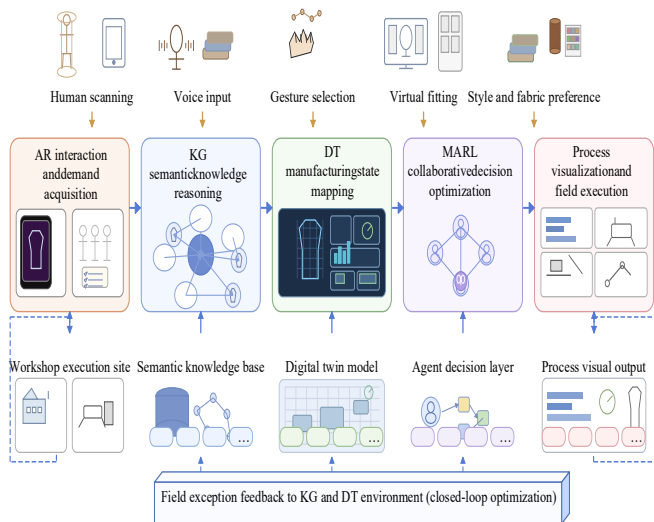


Figure 5. Overall architecture of the KG-DT-MARL clothing customization system, showing the closed-loop data flow from AR interaction and semantic reasoning to DT mapping, collaborative scheduling, process visualization, and anomaly feedback

From Figure 5, the intelligent manufacturing system for clothing customization takes user interaction data as the entry point and obtains customization requirements through human body scanning, voice input, gesture selection and virtual try-on. Then, KG is utilized to organize semantic knowledge such as user, human body, clothing, fabric, process and resources, and complete scheme manufacturability inference. At the manufacturing end, DT maps orders, equipment, processes, quality and logistics status in real time to provide a dynamic decision-making environment for MARL. Ultimately, the process visualization module outputs cutting tips, sewing paths, ironing parameters and quality inspection labels, and feeds back on-site anomalies to the KG and DT environment. The end-to-end data flow proceeds from multimodal AR interaction and KG-based semantic reasoning to DT state mapping, MARL scheduling, process visualization, workshop execution, and anomaly feedback, thereby forming a closed manufacturing loop.

The process visualization module is refreshed synchronously with the DT state at 1s intervals. It displays order progress, process-chain dependencies, workstation load, material inventory, sewing paths, dimensional tolerances, quality alerts, and recommended rescheduling

actions. Operators can filter orders, inspect individual process nodes, acknowledge anomalies, confirm resource assignments, or submit manual adjustment requests. All operator actions are logged and returned to the KG and DT modules. Its operational effect is evaluated through scheme-confirmation time and disturbance-response time in the practical validation experiments. The computational cost mainly arises from KG constraint retrieval, valid-action filtering, and multi-agent policy inference. Constraint-processing time increases approximately linearly with the number of active orders and process constraints, while policy-inference cost increases with the number of agents and network parameters. Since KG queries are indexed and invalid actions are removed before policy evaluation, the online search space can be reduced effectively. The RTX 4090 is mainly used for offline training and large-batch experiments, whereas online scheduling only executes the trained policy and indexed KG queries. However, the minimum hardware configuration and lightweight deployment performance for small and medium-sized enterprises still require further validation.

Recent studies provide relevant engineering foundations for the proposed framework. AR-based DT systems enable real-time visualization and interaction with physical equipment [21], while apparel-oriented DT simulators support assembly-line generation, task assignment, and disturbance handling [22]. Process-planning DT frameworks further connect product, process, and resource knowledge [23], and ontology-based DT construction improves heterogeneous manufacturing resource representation [24]. Building on these studies, the proposed KG-DT-MARL method links AR customization semantics, workshop state mapping, and multi-agent scheduling within a closed-loop garment manufacturing process.

Deployment in a new factory requires initial mapping of garment components, process routes, equipment capabilities, and resource identifiers into the KG and DT models. Process engineers are responsible for validating ontology relations and manufacturing constraints, while automation personnel configure equipment tags and state interfaces. The main engineering effort is concentrated in initial data cleaning, rule verification, and device mapping. Subsequent maintenance is incremental and mainly involves updating process rules, equipment metadata, and workshop-state mappings when products or production resources change. The framework is designed as an extension of existing ERP/MES infrastructure rather than a replacement. Order, material, process, and resource data can be imported through data adapters, while generated schedules, anomaly records, and execution feedback are returned to the MES through service interfaces [25-26]. Therefore, deployment does not require a completely new information system, although interface adaptation and data-field mapping remain necessary for different factories.

3. Results

The experimental platform was configured with an Ubuntu 22.04 operating system, an Intel Core i9-13900K processor, 128 GB memory, and an NVIDIA RTX 4090 GPU. For AR-based immersive interaction acquisition, RGB-D sensing devices and mobile interaction terminals were used to collect body images, depth information, voice commands, gesture trajectories, and fabric-selection operations. The KG semantic modeling module adopted a 128-dimensional embedding space for entity representation and relationship reasoning. The DT module collected equipment status, workstation load, material inventory, process progress, and quality information, with the virtual state updated every 1s. The MARL scheduling module contained five agents, and each agent was implemented with two hidden layers containing 256 and 128 neurons. Adam optimizer was employed with a learning rate of 3×10^{-4} , a discount factor of 0.95, a batch size of 128, and 500 training episodes. The experimental data sources included laboratory-collected clothing customization interaction samples and the public clothing image dataset DeepFashion2. Laboratory data was used for modeling body size, voice commands, gesture trajectories, and fabric preferences, while DeepFashion2 was used for garment component recognition, style category matching, and visual semantic feature training. The visual, speech, gesture, and style features were encoded into 256-, 128-, 128-, and 64-dimensional vectors and projected into a 256-dimensional fused representation.

3.1. Performance analysis of KG interactive semantic modeling

To assess the effectiveness of the proposed KG-DT-MARL method in the interaction semantic modeling module, the study only selected AR interaction data for module-level validation, and the test included four semantic sub-tasks: requirement analysis, entity recognition, relationship recognition, and entity fusion. A rule-based Manufacturing Execution System (Rule-MES), a Knowledge Graph-Reinforcement Learning (KG-RL) method, and a Digital Twin-Proximal Policy Optimization (DT-PPO) method were selected as comparative approaches. The results are shown in Figure 6.

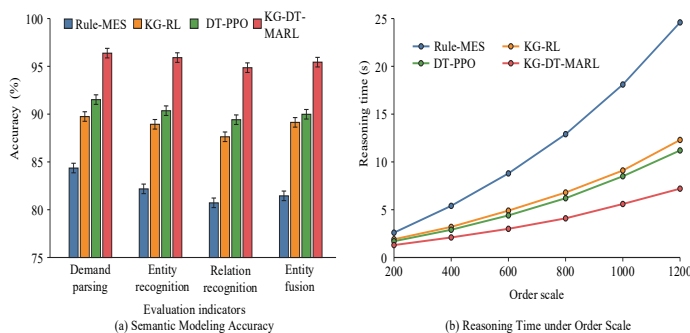


Figure 6. Robustness comparison of KG interactive semantic modeling under interaction noise disturbance

As shown in Figure 6 (a), KG-DT-MARL achieved the best results in demand resolution, entity recognition, relationship recognition, and entity fusion in the semantic modeling module-level tests, with requirement parsing accuracy reaching 96.38% and entity fusion accuracy reaching 95.44%. It was significantly higher than the 84.36% and 81.45% of Rule-MES. As shown in Figure 6(b), the inference time for all methods exhibited an upward trend as the order volume increases from 200 to 1,200; however, KG-DT-MARL showed the slowest growth, with an inference time of 7.2 s at a volume of 1,200 orders, lower than the 12.3 s for KG-RL and 11.2 s for DT-PPO, and significantly lower than the 24.6 s for Rule-MES. The reason is that KG-DT-MARL narrows the search range of candidate entities and relations through KG and optimizes the inference path with the DT-MARL feedback mechanism, thus maintaining good semantic inference efficiency under large orders. A sensitivity analysis was further conducted by varying each of α , β , and γ within ± 0.10 of the selected values at intervals of 0.05, while maintaining $\alpha + \beta + \gamma = 1$. Entity-fusion F1-score was reported as the mean and standard deviation over five random seeds. The selected combination provided the highest validation performance, whereas moderate coefficient variations did not change the overall ranking of the compared methods.

3.2. KG-DT-MARL manufacturing co-optimization performance analysis

To assess the scheduling efficiency, dynamic response stability and resource allocation effect of KG-DT-MARL in collaborative optimization of clothing customization manufacturing, comparative experiments were conducted with different order scales and disturbance scenarios, and the findings are denoted in Figure 7.

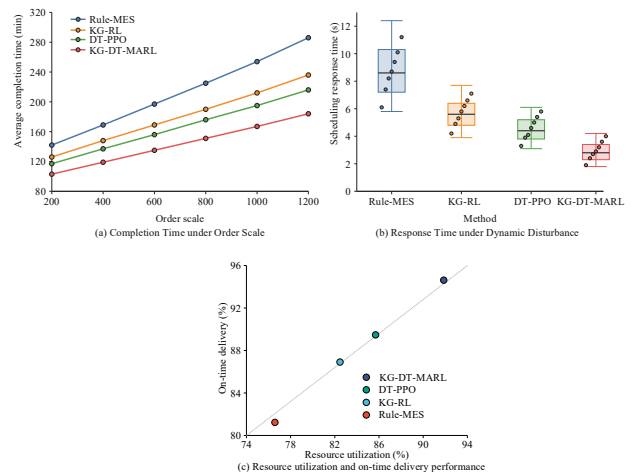


Figure 7. DT-MARL manufacturing collaborative optimization performance

In Figure 7(a), the average completion time for each method increased gradually as the order volume rises from 200 to 1,200 orders. However, KG-DT-MARL consistently maintained the lowest level, recording 184 minutes at 1,200 orders, lower than the 216 minutes for DT-PPO, 236 minutes for KG-RL, and 286 minutes for Rule-MES. In Figure 7 (b), the median scheduling response time of KG-DT-MARL was 2.8 s, significantly lower than that of DT-PPO at 4.4 s, KG-RL at 5.6 s, and Rule-MES at 8.6 s, and the distribution was more concentrated, indicating that it was more stable in response to disturbances such as equipment occupancy, material shortage, and abnormal rework. In Figure 7 (c), the resource utilization rate and order on-time delivery rate of KG-DT-MARL reached 95.86% and 94.62% respectively, which were in the optimal range. The reason is that KG constrains the process path in advance, DT maps the workshop status in real time, and MARL further optimizes the joint order, equipment, process and quality.

After completing the validation of the semantic modeling module, the performance of different methods in terms of clothing customization demand analysis, process generation, resource allocation and dynamic response was further comprehensively validated from the perspective of the end-to-end clothing customization manufacturing process, and the findings are shown in Table 1.

Table 1. Comparison of comprehensive performance of various methods for clothing customization manufacturing

Method	Rule-MES	KG-RL	DT-PPO	KG-DT-MARL
Demand parsing accuracy(%)	84.36	89.75	91.52	96.38
Process-chain generation accuracy(%)	82.41	88.63	90.12	95.74
Resource utilization(%)	76.58	82.47	85.69	91.86
On-time delivery rate(%)	81.23	86.91	89.47	94.62
Average completion time(min)	286	236	216	184
Average response time(s)	8.6	5.6	4.4	2.8
Rework rate(%)	8.64	6.28	5.41	3.27

As shown in Table 1, KG-DT-MARL performed best in all seven indicators in the end-to-end manufacturing comprehensive test, with requirement parsing accuracy reaching 96.38%, process chain generation accuracy reaching 95.74%, resource utilization and order on-time delivery rates reaching 91.86% and 94.62% respectively. It was significantly higher than the 76.58% and 81.23% of Rule-MES. Meanwhile, KG-DT-MARL reduced the average completion time to 184 minutes, the average response time to just 2.8 seconds, and the rework rate to 3.27%, indicating that the method not only improved the quality of custom solution analysis and process generation, but also enhanced the scheduling efficiency at the manufacturing end. The reason for this result is that KG can strengthen the semantic association between user requirements, garment parts, process rules and manufacturing resources, DT can map the workshop status in real time, and MARL can further achieve multi-resource

collaborative decision-making, thereby reducing the risk of waiting, conflict and rework.

3.3. Practical application and multi-condition validation

To test the adaptability of KG-DT-MARL in different practical application scenarios, six verification scenarios were set up in the study, where S1 was a regular custom order, S2 was an AR interactive modification, S3 was an emergency insertion order, S4 was equipment occupation, S5 was fabric loss, and S6 was quality rework. The outcomes are denoted in Table 2. The results in Table 2 were obtained from laboratory-based controlled validation rather than from long-term factory production or purely synthetic simulation. Laboratory-collected AR interaction records and customization orders were used as system inputs. S1 and S2 were based on regular customization and actual AR interaction modification, respectively. S3-S6 were constructed by controlled disturbance injection in the DT environment, including urgent-order insertion, temporary workstation unavailability, reduced fabric inventory, and out-of-tolerance quality records. The resulting process-generation and scheduling indicators were recorded from the closed-loop KG-DT-MARL prototype.

Table 2. Practical validation results of KG-DT-MARL under different application scenarios

Scenario	S1	S2	S3	S4	S5	S6
Scheme confirmation time(min)	6.82	5.37	7.94	8.26	7.48	9.15
Process-chain generation accuracy(%)	95.31	96.24	94.16	93.87	94.72	93.28
On-time delivery rate(%)	94.18	94.63	92.85	91.74	92.46	90.63
Average response time(s)	2.58	2.36	2.91	3.18	2.84	3.42
Rework rate(%)	3.46	3.18	3.76	4.12	3.85	4.68

In Table 2, KG-DT-MARL maintained good validation results in various application scenarios. Among them, the scheme confirmation time for the S2 AR interactive modification scenario was the shortest, at 5.37 min, the process chain generation accuracy reached 96.24%, and the average response time was only 2.36 s. In contrast, the scheme confirmation time for the S6 quality rework scenario increased to 9.15 minutes, the order on-time delivery rate dropped to 90.63%, and the rework rate rose to 4.68%, mainly due to size deviations triggering local process backtracking and resource reallocation. Overall, the system is able to maintain an on-time delivery rate of over 90% even under disturbance conditions such as emergency insertion, equipment occupancy, and fabric loss, indicating that DT-MARL has strong dynamic scheduling and on-site adaptability. The framework performs less effectively when interaction inputs are severely noisy, KG process rules are incomplete, DT states are outdated, or communication

interruptions persist beyond the synchronization interval. Under these conditions, incorrect semantic parameters or delayed workshop states may reduce process-chain accuracy and increase rescheduling time. The results for equipment occupation and quality rework also indicate that the advantage decreases when extensive process backtracking and resource reallocation are required. Therefore, manual confirmation and rule-based fallback scheduling are retained for low-confidence or disconnected conditions. Compared with KG-RL, the proposed framework additionally uses DT-synchronized workshop states to update scheduling decisions in real time. Compared with DT-PPO, it introduces KG-derived process constraints and multi-agent coordination to restrict infeasible routes and jointly optimize orders, processes, resources, and quality. Therefore, the performance improvement results from the coordinated coupling of semantic constraints, virtual-real state mapping, and collaborative scheduling rather than from a single module. Accordingly, the observed improvements should be attributed to the combined effect of AR-based requirement acquisition, KG semantic constraints, DT state mapping, and MARL collaborative scheduling, rather than to any single module.

To quantitatively isolate the contribution of each component, four leave-one-module-out variants were evaluated using the same test set, order scale, disturbance settings, and evaluation protocol as the complete framework. The ablation results are presented in Table 3.

Table 3. Ablation results of different components in the KG-DT-MARL framework

Model variant	Full KG-DT-MARL	w/o AR	w/o KG	w/o DT	w/o MARL
Requirement parsing accuracy (%)	96.38	90.42	93.84	95.62	95.91
Process-chain generation accuracy (%)	95.74	92.36	89.47	92.74	93.18
Resource utilization (%)	91.86	89.47	87.65	86.84	82.51
On-time delivery rate (%)	94.62	92.18	90.36	89.15	86.27
Average completion time (min)	184	198	207	219	238
Average response time (s)	2.8	3.54	4.21	5.08	6.34
Rework rate (%)	3.27	4.08	4.72	4.86	5.96

As shown in Table 3, the complete KG-DT-MARL framework achieved the best overall performance across all seven indicators. Removing the AR interaction module reduced the requirement-parsing accuracy from 96.38% to 90.42%, while the process-chain generation accuracy and on-time delivery rate decreased to 92.36% and 92.18%, respectively. This result indicates that AR mainly contributes to accurate and efficient acquisition of multimodal customization requirements. Removing the KG reduced the process-chain generation accuracy to 89.47%

and increased the rework rate from 3.27% to 4.72%, demonstrating that semantic constraints and manufacturability reasoning are essential for generating feasible process routes. When the DT was replaced with periodically updated static workshop states, resource utilization and on-time delivery rate decreased to 86.84% and 89.15%, while the average response time increased to 5.08 s, confirming the importance of real-time virtual-physical synchronization. Replacing MARL with priority-rule scheduling caused the largest scheduling degradation: resource utilization and on-time delivery rate fell to 82.51% and 86.27%, average completion time increased to 238 min, and the rework rate rose to 5.96%. These results show that AR, KG, DT, and MARL contribute primarily to requirement acquisition, process feasibility, real-time state perception, and dynamic resource coordination, respectively. Their coordinated integration enables the complete framework to achieve balanced end-to-end performance.

To validate the interaction efficiency, process generation accuracy and multi-scenario adaptability of KG-DT-MARL in actual clothing customization applications, further user-end interaction verification and production-end application verification experiments were set up, and the findings are denoted in Figure 8.

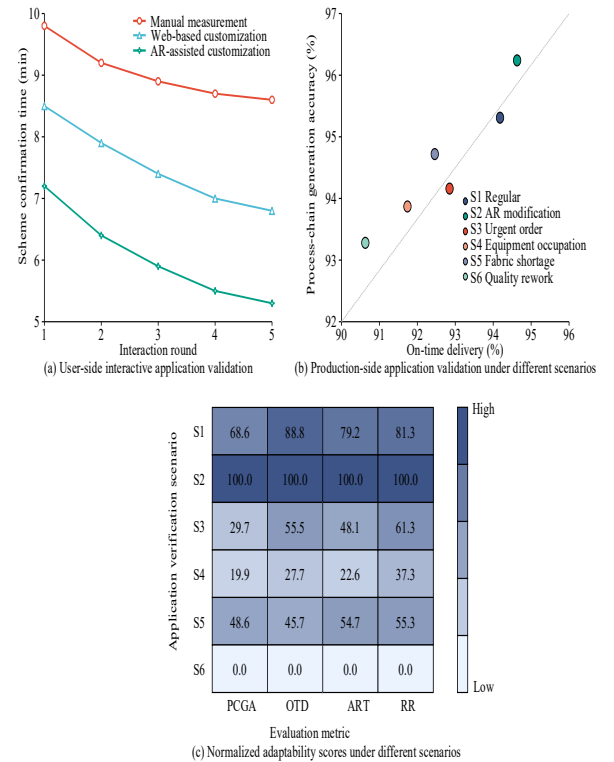


Figure 8. Practical application and multi-condition validation results

From Figure 8 (a), in client-side interactive validation, the validation time of the three customized methods decreased with the increase of interaction rounds. Among them, manual volume measurement always took the longest time,

about 9.8 minutes for the first round and still about 8.6 minutes for the fifth round. Web customization dropped from about 8.4 minutes to 6.8 minutes. AR customization saw the most significant drop, from about 7.2 minutes to 5.3 minutes. In Figure 8 (b), under different production-end application scenarios, the accuracy of process chain generation was generally positively correlated with the on-time delivery rate of orders. The AR modification scenario performed the best, with an on-time delivery rate of approximately 94.63% and an accuracy of process chain generation of approximately 96.24%. The quality rework scenario performed relatively poorly, with an on-time delivery rate of approximately 90.63% and an accuracy rate of approximately 93.28%. In Figure 8 (c), the normalized adaptability score reached 100.0 for all four indicators in the S2 scenario. The score for each item in the S6 scenario was 0.0, indicating that quality rework has the greatest impact on process generation, on-delivery, response, and rework control.

4. Conclusion

This study developed a garment-specific KG-DT-MARL framework that connects multimodal AR interaction with process generation and collaborative manufacturing scheduling. The KG organized customization and process knowledge, the DT synchronized workshop states, and MARL selected feasible process and resource actions under semantic and operational constraints. Comparative and multi-scenario experiments showed that the integrated framework improves requirement parsing, process-chain generation, scheduling response, delivery performance, and rework control over the selected baselines. The results show that KG-DT-MARL can improve interactive parsing, process generation, and dynamic scheduling. However, the current validation mainly relies on laboratory-collected data and a public clothing image dataset, and does not fully represent noisy multimodal inputs, incomplete DT updates, communication interruptions, or long-term multi-line production. Future work will validate the framework using real factory order flows and quality records, develop asynchronous DT synchronization and lightweight MARL deployment, and evaluate ERP/MES integration across multiple workshops and shifts.

References

- [1] Zhang J, Hu Y Y, Zhang M Y, Hu X Y, Lu L S, Sha S, Xiao J, Jiang X W. Non-contact body measurement for clothing customization based on 2D images: A systematic review [J]. *Journal of Textile Research Journal*, 2025, 95 (19-20) : 2452-2471. The DOI: 10.1177/00405175251318629.
- [2] Lyu Y R, Wang Z H, Ye Q W, Sun Y X, Chao J. Body data-driven garment pattern construction in digital fashion innovations: A review [J]. *Journal of Textile Research Journal*, 2026, 96 (11-12) : 1299-1335. The DOI: 10.1177/00405175251352800.
- [3] Guo Y X, Sun L. Garment pattern generation method based on Diffusion Model and 3D reconstruction technology[J]. *Textile Research Journal*, 2025, 95 (23-24) : 2866-2881. The DOI: 10.1177/00405175251328296.
- [4] Sun Y X, Hao Z H, Wang Z H, Jin J, Ye Q W, Lyu Y R. Deep learning for 3D garment generation: A review [J]. *Journal of Textile Research Journal*, 2025, 95 (23-24) : 2882-2908. The DOI: 10.1177/00405175251335188.
- [5] Yu J J, Shi H, Duan W J. Personalized digital human modeling in the customized clothing industry under Industry 5.0[J]. *Textile Research Journal*, 2025, 95 (21, 22) : 2679-2690. The DOI: 10.1177/00405175251318243.
- [6] Shi H, Yu J J, Duan T. Advances in personalized modelling and virtual display of ethnic clothing for intelligent customization[J]. *AUTEX Research Journal*, 2024, 24(1):28-41. DOI:10.1515/aut-2023-0040.
- [7] Han H S, Park C K. An optimized production assignment algorithm for custom-made garments[J]. *Advances in Production Engineering & Management*, 2025, 20 (2) : 239-253. The DOI: 10.14743 / apem2025.2.538.
- [8] Cui J X, Lou R D, Mantelet F, Segonds F. Integration of additive manufacturing and augmented reality in early design phases: A way to foster remote creativity[J]. *International Journal on Interactive Design and Manufacturing*, 2024, 18(2):609-625. DOI:10.1007/s12008-023-01629-6.
- [9] Ozbek A. Analysis of Turkish consumers' customized clothing purchase intention[J]. *Textile and Apparel*, 2025 35 (1) : 64-75. The DOI: 10.32710 / tekstilvekonfeksiyon.1472514.
- [10] Xiao Y Z, Zheng S, Shi J C, Du X D, Hong J. Knowledge graph-based manufacturing process planning: A state - of - the - art review [J]. *Journal of Manufacturing Systems*, 2023, 70 (1) : 417-435. The DOI: 10.1016 / j.j. Msy 2023.08.006.
- [11] Kaven L, Huke P, Goppert A Schmitt R H. Multi agent reinforcement learning for online layout planning and scheduling in flexible assembly systems[J]. *Journal of Intelligent Manufacturing*, 2024, 35(8):3917-3936. DOI:10.1007/s10845-023-02309-8.
- [12] Meyers B, Vangheluwe H, Lietaert P, Vanderhulst G, Van Noten J, Schaffers M, Maes D, Gadeyne K. Towards a knowledge graph framework for ad hoc analysis in manufacturing[J]. *Journal of Intelligent Manufacturing*, 2024, 35(8):3731-3752. DOI:10.1007/s10845-023-02319-6.
- [13] Zhang Z F, Qu T, Huang G Q, Zhao K, Zhang K, Li M X, Zhang Y H, Liu L, Zhong H H. Digital twin and blockchain-enabled trusted optimal-state synchronized control approach for distributed smart manufacturing system in social manufacturing[J]. *Journal of Manufacturing Systems*, 2024, 76 (1) : 385-410. The DOI: 10.1016/j.jmsy.2024.08.004.
- [14] Didden J B H C, Dang Q V, Adan I J B F. Enhancing stability and robustness in online machine shop scheduling: A multi-agent system and negotiation-based approach for handling machine downtime in industry 4.0[J]. *European Journal of Operational Research*, 2024, 316 (2) : 569-583. The DOI: 10.1016/j.ejor.2024.02.006.
- [15] Dautère-Pères S, Ding J W, Shen L J, Tamssaouet K. The flexible job shop scheduling problem: A review[J]. *European Journal of Operational Research*, 2024, 314 (2) : 409-432. The DOI: 10.1016/j.ejor.2023.05.017.
- [16] Wang L K, Wang Z, Gumma K, Turner A, Ratchev S. Multi-agent cooperative swarm learning for dynamic layout optimisation of reconfigurable robotic assembly cells based on digital twin[J]. *Journal of Intelligent Manufacturing*, 2025, 36 (5) : 2959-2982. The DOI: 10.1007/s10845-023-02229-7.
- [17] Pulikottil T, Estrada-Jimenez L A, Ur Rehman H, Mo F, Nikghadam-Hojjati S, Barata J. Agent-based manufacturing: Review and expert evaluation[J]. *The International Journal of*

- Advanced Manufacturing Technology, 2023, 127 (5-6) : 2151-2180. The DOI: 10.1007/s00170-023-11517-8.
- [18] Li Y Q, Liu X R, Starly B. Manufacturing service capability prediction with Graph Neural Networks[J]. Journal of Manufacturing Systems, 2024, 74 (1) : 291-301. The DOI: 10.1016/j.jmsy.2024.03.010.
- [19] Jing X, Yao X F, Liu M, Zhou J J. Multi-agent reinforcement learning based on graph convolutional network for flexible job shop scheduling[J]. Journal of Intelligent Manufacturing, 2024, 35 (1): 75-93. The DOI: 10.1007/s10845-022-02037-5.
- [20] Wang R, Wang G, Sun J, Deng F, Chen J. Flexible job shop scheduling via dual attention network-based reinforcement learning[J]. IEEE Transactions on Neural Networks and Learning Systems, 2024, 35 (3): 3091-3102. The DOI: 10.1109/TNNLS.2023.3306421.
- [21] Pitzalis R F, Giordano A, Di Spigno A, Cowell A, Niculita O, Berselli G. Application of augmented reality-based digital twin approaches: a case study to industrial equipment[J]. The International Journal of Advanced Manufacturing Technology, 2025, 138(7-8):3747-3763. DOI:10.1007/s00170-025-15755-w.
- [22] Kim M, Kim S. Development of a dedicated process simulator for the digital twin in apparel manufacturing: a case study[J]. International Journal of Clothing Science and Technology, 2024, 36(4):629-645. DOI:10.1108/IJCST-01-2024-0017.
- [23] Wagner S, Gonnermann C, Wegmann M, Listl F, Reinhart G, Weyrich M. From framework to industrial implementation: the digital twin in process planning[J]. Journal of Intelligent Manufacturing, 2024, 35(8):3793-3813. DOI:10.1007/s10845-023-02268-0.
- [24] Boroukhian T, Supyen K, Samson J B, Bashyal A, Wicaksono H. Integrating 3D object detection with ontologies for accurate digital twin creation in manufacturing systems[J]. The International Journal of Advanced Manufacturing Technology, 2025, 140(9-10):4679-4711. DOI:10.1007/s00170-025-16548-x.
- [25] Wan Y W, Liu Y, Chen Z Y, Chen C, Li X Y, Hu F, Packianather M. Making knowledge graphs work for smart manufacturing: Research topics, applications and prospects. Journal of Manufacturing Systems, 2024, 76:103-132. DOI:10.1016/j.jmsy.2024.07.009.
- [26] Kim D B, Bajestani M S, Lee J Y, Shin S J, Kim G Y, Sajadieh S M M, Noh S. Human-in-the-loop in smart manufacturing (H-SM): A review and perspective. Journal of Manufacturing Systems, 2025, 82:178-199. DOI:10.1016/j.jmsy.2025.05.020.