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Knowledge graph is used to construct the association network of clothing design elements and realize intelligent recommendation design

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SUMMARY: *In order to solve the problems of scattered relationships between elements in fashion design, the difficulty of structured expression of user preferences, and the lack of interpretation of recommendation results, this paper proposes a knowledge graph based method for the construction of clothing design element association network and intelligent recommendation. The design, color, material, process and scene semantics are integrated into the unified computing framework. Through multi-source data collection, label generation, relationship extraction, user preference clustering and scheme combination optimization, a complete technology chain is formed from knowledge organization, association reasoning to recommendation output. Based on 2680 clothing samples and 18642 user interaction records, the experiment constructs a clothing design knowledge graph, and uses the rule response space to depict the differences between user groups. The results show that the F1 value of the proposed method in the construction of the element association network reaches 0.857, the contour coefficient of user clustering is 0.64 when K=5, the average acceptance rate of the recommendation scheme is 0.794, and the rule overlap rate and output consistency in the cross-task test remain above 0.79. The results show that the knowledge graph can effectively enhance the integrity of the relationship expression of clothing design elements, the stability and interpretability of the recommendation results, and provide a feasible path for the implementation of intelligent clothing design assistant systems.*

KEYWORDS: *Knowledge graph; Fashion design; Element correlation network; Intelligent recommendation*

1 Introduction

With the continuous advancement of the digital transformation of the clothing industry, design activities are no longer limited to the selection of style driven by designer's experience, but gradually enter the stage supported by data organization, relational computing and intelligent generation. Although the existing research on clothing intelligence has made rapid progress in collocation prediction, style recognition and recommendation decision, many methods are still mainly based on isolated attribute matching or shallow similarity calculation, and the deep semantic connections between styles, colors, materials, processes and wearing scenes are insufficient to describe, which makes it difficult to form a stable, interpretable and transferable design knowledge structure [1]. In the context of continuous accumulation of large-scale clothing images, text labels and consumer feedback, how to transform scattered design information into a computable, reasonable and recommended element association network has

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become a key issue in the research of intelligent clothing design [2].

From the existing results, deep learning improves the accuracy of clothing compatibility judgment and collocation recognition, but the model often focuses on the result prediction, lacks the explanation of "why recommended" and "which elements work together", and is prone to semantic drift in cross-style and cross-task scenarios [3]. Heterogeneous graph network and graph neural network provide a new path for modeling clothing item relationship, which can express the complementarity and constraint between elements to a certain extent. However, without domain knowledge injection, the graph structure is still easy to stay at the statistical co-occurrence level, and it is difficult to cover the hierarchical relationship and rule logic in design semantics [4, 5]. At the same time, research on multimodal knowledge graph and knowledge graph recommendation shows that integrating entities, attributes, relationships and external semantics into a unified representation space is helpful to enhance the association reasoning ability and explanation ability of the recommendation system, which provides a referable computational framework for the networked modeling of fashion design elements [6, 7].

Based on this understanding, this paper focuses on the structural expression and intelligent recommendation of fashion design elements, and constructs a complete technical chain of "data acquisition, label generation, knowledge graph construction, relation reasoning, preference recognition and scheme recommendation". This paper organizes the fashion, color, material and process information into the pattern layer and the entity layer of the knowledge graph, establishes the multi-dimensional connections between the elements through relationship extraction and network modeling, and combines user behavior data and clustering analysis to identify differentiated design preferences, and then realizes the combination optimization and intelligent generation of design schemes in the recommendation end. Compared with the practice of relying only on image similarity or single compatibility score, this method puts more emphasis on the explicit organization of design knowledge, the traceable expression of association paths, and the interpretable output of recommendation results [8, 9]. The core value of this paper is to build a computational model that connects design knowledge, user preferences and generative decisions, rather than merely improving local prediction indicators, so as to provide a more logical and practical implementation basis for intelligent clothing design assistant systems [10, 11].

2 Related Research

Focusing on intelligent fashion design, existing research mainly focuses on clothing compatibility judgment, collocation recommendation and multimodal semantic understanding. Ding et al. systematically reviewed fashion recommendation computing technology and pointed out that clothing recommendation has gradually shifted from collaborative filtering in the early stage to a comprehensive modeling framework integrating image, text and attribute information, but it is still weak in explicit expression of design knowledge [11]. Based on the development of fashion intelligence, Liu et al. believe that clothing research in the big data environment is moving from single item recognition to style understanding and decision support, but the semantic relationship between design elements has not been fully structured representation [12]. Shimizu et al. tried to use images and abstract labels to jointly explain clothing combinations, which provided a fine-grained description path for semantic analysis of dress matching [13]. Balim and Ozkan used deep learning models to diagnose clothing compatibility and improved the accuracy of combination recognition [14]. However, most methods still regard the recommendation object as the matching result between feature vectors, and lack the expression of the hierarchical relationship between style, color, material, process and scene constraints.

Although the model can give the results, it is difficult to explain the internal logic of the formation of the recommendation.

With the development of graph structure learning, scholars begin to use heterogeneous graph networks, graph neural networks, and complementary matching mechanisms to describe the association between clothing items. Zhou et al. proposed attribute-aware heterogeneous graph network, which incorporated clothing attributes and interaction relationships into the representation space together to enhance the compatibility prediction ability [15]. Wang et al. learn compatible knowledge from the perspective of complementary clothing matching, so that the collocation recommendation is no longer limited to surface similarity, but pays more attention to the combination synergy effect [16]. Lu et al. further introduced heterogeneous graph neural network into clothing collocation prediction to improve the information dissemination effect in complex relationship scenes [17]. This shows that the graph model is indeed suitable for dealing with multi-entity association problems in fashion design. However, most of the "graphs" in the existing work are based on statistical co-occurrence or interaction records, and the explicit embedding of domain knowledge is still insufficient, and the reasoning and traceable semantic network between design elements has not yet been truly formed.

In the combination of knowledge graph and recommendation system, the research on multimodal knowledge graph has provided a more mature theoretical support for complex object modeling. Zhu et al. pointed out that multi-modal knowledge graphs can unify visual objects, textual descriptions and structural relations into the same knowledge space, thereby enhancing entity representation and cross-modal reasoning capabilities [18]. Guo et al reviewed the development of knowledge graph recommendation systems, and believed that knowledge association could not only alleviate the problem of data sparsity, but also improve the interpretability of recommendation results [19]. Gao et al. summarized the application challenges of graph neural networks in recommendation, emphasizing that structural modeling and preference propagation are the key links to improve the quality of recommendation [20]. In the direction of interpretable recommendation, Shimizu et al. integrated large-scale side information through an improved knowledge graph attention network to achieve a more transparent expression of recommendation paths [21]. However, there are still obvious gaps in the research of fashion design tasks. On the one hand, the construction of knowledge graph of design elements mostly stays at the level of product labels, lacking the schema level organization oriented to design semantics. On the other hand, user preference identification, element relationship reasoning and design scheme generation have not been integrated into the same computing chain. Because of this, how to construct a fashion design element correlation network and realize interpretable intelligent recommendation on this basis is still a core problem that needs further breakthrough in current research.

3 Association modeling and intelligent recommendation method of fashion design elements

3.1 Construction of pattern layer and entity layer of knowledge graph of garment design elements

Intelligent recommendation of fashion design elements is not a simple matching of isolated labels, but to integrate style, color, material, craft, style semantics and usage scenarios into the same computing framework, so that design knowledge can be unified representation, associated reasoning, and participate in subsequent combination decisions. Based on this idea, this paper divides the fashion design knowledge graph into the pattern layer and the entity layer. The schema layer is used to define domain concepts, attribute boundaries and relationship constraints, and the entity layer is used to carry concrete clothing samples, design element instances and user interaction objects. Together, they form the basis of structured representation of fashion design knowledge.

In terms of formal representation, this paper defines the knowledge graph as

$$\mathcal{G} = (\mathcal{V}, \mathcal{R}, \mathcal{A}, \mathcal{T}) \quad (1)$$

Here, V represents the set of entities, R represents the set of relations, A represents the set of attributes, and T represents the set of triples. Any unit of design knowledge can be written as

$$\tau = (\mathrm{h}, \mathrm{r}, \mathrm{t}), \quad \mathrm{h}, \mathrm{t} \in \mathcal{V}, \mathrm{r} \in \mathcal{R} \quad (2)$$

where, h is the head entity, t is the tail entity, and r is the semantic relation between them. For example, "A-line skirt -- hasColor -- cream white" and "wool coat -- usesFabric -- cashmere blend" can all be mapped to standard triples. In order to ensure the scalability of the pattern layer, this paper organizes the core concepts into eight types of nodes: clothing category -- shape contour -- color system -- material type -- process method -- style label -- seasonal scene -- user preference, and sets up the relationships of "belong to", "adopt", "fit", "collocation", "derived from" and "preferred to". In order to express element dependency, cooperativity and constraint in subsequent reasoning. As shown in Table 1, the schema layer does not directly store specific samples, but is responsible for limiting node types, key attributes and relationship semantics, and providing unified rules for the entity layer to access real design data.

Table 1: Schematic diagram of schema layer and entity layer structure of clothing design knowledge graph

Level	Node Type	Key Attributes	Main Relationships	Example
Schema layer	Clothing category	category_id, name	belongsToStyle, suitableForScene	Dress, trench coat, suit
Schema layer	Design element	silhouette, color, fabric, craft	hasColor, usesFabric, adoptsCraft	A-line, off-white, silk, pleating
Schema layer	Scene semantics	season, occasion, function	suitableFor, conflictsWith	Spring, commuting, formalwear scene
Schema layer	User preference	preference_tag, aesthetic_type	prefers, avoids	Minimalist, vintage, urban style
Entity layer	Clothing item	item_id, image, text	hasElement, matchesWith	Item_0231
Entity layer	Design scheme	scheme_id, score	composedOf, recommendedTo	Scheme_014
Entity layer	User instance	user_id, behavior_log	clicked, collected, preferred	User_078

When building the entity layer, considering that the clothing object has structural attributes, visual features and text semantics at the same time, this paper establishes a unified initial representation for each entity:

$$\mathrm{z_i} = \mathrm{W_s s_i} + \mathrm{W_v v_i} + \mathrm{W_t t_i} \quad (3)$$

$\mathrm{s_i}$ is a structured attribute vector, which contains discrete label codes such as category, plate type, fabric and process. $\mathrm{v_i}$ is the feature extracted from the clothing image by the visual coding network. t_i is the semantic vector of product description, design description and style text. W_s、W_v、W_t are the mapping matrices of the corresponding modes. In this way, the entity layer is no longer just a static sample library, but a node representation space that can be directly interfaced with the graph reasoning model. In order to reduce the noise caused by synonymous names, label fragmentation, and artificial naming differences, we perform term normalization, color standard mapping, material alias merging, and process level re-coding before the entity is added to the graph, so that near-meaning color names such as "beige", "cream", and "ivory" are converged to a unified color node, which improves the density and relationship stability of the graph.

Through the above construction method, the schema layer provides the classification framework and relational grammar of clothing design knowledge, and the entity layer integrates real samples, user preferences and design solutions into a unified graph space, forming the basis of graph that "concepts can be defined, instances can be attached, and relations can be reason about". This structure provides a stable data interface for subsequent design element relationship extraction, user preference clustering and intelligent recommendation generation, and makes the recommendation results more interpretable and traceable.

3.2 Garment style, color, material and process data collection and label generation

Whether the association network of clothing design elements can be established largely depends on whether the underlying data is complete and whether the labels are stable. If the style, color, material and process still exist in loose text or non-uniform naming, the entity alignment and relationship reasoning in the subsequent knowledge graph are prone to semantic drift. Based on this consideration, this paper sets the data collection objects as five types of information: clothing images, commodity copy, design instructions, fabric files and process records, and organizes them into a multi-source sample collection

$$\mathcal{D} = \{(I_i, T_i, F_i, C_i)\}_{i=1}^{N} \tag{4}$$

Here, I_i represents the garment image of the ith sample, T_i represents the text description, F_i represents the fabric information, and C_i represents the process instructions. Through this structure, design information that was originally scattered in different sources is transformed into standard input that can be processed in parallel.

In the specific processing process, the style labels mainly come from the joint results of image contour recognition and text rule extraction. Firstly, the system performs object segmentation and region clipping on the garment master image, and then extracts the visual features such as collar type, sleeve type, garment length, profile and component combination. The color labels are clustered in HSV color space and mapped to a unified color system according to the comprehensive color chart. Material and craft tags rely more on text side information, and keywords such as "cotton and linen", "chiffon", "knitted", "pleated", "embroidery" and "crimped" are extracted through word segmentation, term dictionary matching and context discrimination. Since the dimensions of signals from different sources are not consistent, this paper uses range standardization for all types of evidence values:

$$\tilde{x}_i^{(k)} = \frac{x_i^{(k)} - \min(x^{(k)})}{\max(x^{(k)}) - \min(x^{(k)})} \tag{5}$$

where $x_i^{(k)}$ represents the original score of sample i on the KTH attribute, and $\tilde{x}_i^{(k)} \in [0,1]$ is the normalized result. After this process, the image detection intensity, text matching confidence and manual verification score can enter the same calculation interval, which is convenient for subsequent fusion. In order to reduce the noise caused by misjudgment of a single modality, this paper further constructs the label fusion score:

$$s_i^{(k)} = \alpha\tilde{x}_{i,v}^{(k)} + \beta\tilde{x}_{i,t}^{(k)} + \gamma\tilde{x}_{i,m}^{(k)}, \quad \alpha + \beta + \gamma = 1 \tag{6}$$

Here, $\tilde{x}_{i,v}^{(k)}$、$\tilde{x}_{i,t}^{(k)}$、$\tilde{x}_{i,m}^{(k)}$ represent the normalized results of visual recognition, text extraction and human review on attribute k, respectively. Combining the results of small-scale pre-experiments and cross-validation, α=0.45, β=0.35, γ=0.20 are selected in this paper. This means that the system pays more attention to the ability of image side to distinguish style and color, while retaining the complementary role of text and manual verification for material and process information. As shown in Table 2, different samples can form label confidence distributions with clear boundaries after multi-source evidence fusion, which provides a more stable data basis for subsequent entity mapping and relationship modeling.

Table 2: Examples of fusion of multi-source acquisition results and labels for clothing design elements

Sample ID	Style Label	Main Color Label	Material Label	Craft Label	Visual Score	Text Score	Review Score	Fusion Confidence
S01	A-line dress	Off-white	Chiffon	Pleating	0.91	0.84	0.88	0.879
S02	Cropped jacket	Dark gray	Denim	Washed finish	0.86	0.79	0.82	0.823
S03	Straight skirt	Light blue	Cotton-linen	Patchwork	0.78	0.81	0.85	0.806
S04	Loose shirt	Khaki	Linen	Embroidery	0.74	0.89	0.87	0.824
S05	Slim-fit suit	Black	Wool blend	Three-dimensional tailoring	0.88	0.86	0.90	0.878

After fusing the scores, the system uses a threshold function to convert the continuous scores into discrete labels:

$$y_i^{(k)} = \begin{cases} 1, & s_i^{(k)} \geq \theta \\ 0, & s_i^{(k)} < \theta \end{cases} \tag{7}$$

Here, θ is the threshold of label validity, which is set to 0.75 in this paper. The fusion results in Table 2 show that most high-frequency design elements can be accurately mapped into structured labels under the unified standard, while low-confidence samples will be retained as the state to be verified, rather than being directly written into the graph. This processing method avoids the error diffusion caused by the premature solidification of labels, and also enables the four core elements of style, color, material and technology to enter the subsequent relationship extraction and association network construction process in a consistent format.

3.3 Association Extraction and network Modeling of design Elements Based on Knowledge Graph

After the generation of clothing style, color, material and process labels, the research task shifts from "element recognition" to "relationship expression". For fashion design, what really affects the quality of recommendation is not only the single element itself, but also whether there are stable combination rules, style dependencies and scene constraints between elements. Therefore, based on the labeled sample set $\mathcal{D} = \{d_i\}_{i=1}^{N}$, this paper maps the design elements in the sample to the entity set $\mathcal{E} = \{e_1, e_2, \dots, e_n\}$, and construct the set of candidate relations $\mathcal{R} = \{r_1, r_2, \dots, r_m\}$. Any candidate triple can be expressed as

$$\tau_{ij}^{(k)} = (e_i, r_k, e_j) \tag{8}$$

Among them, e_i and e_j respectively represent two entities of costume design elements, and r_k represents the semantic relationship between them, such as "color coordination", "material adaptation", "process enhancement", "style consistency" or "scene matching". The relation extraction does not directly depend on the single co-occurrence number, but considers the co-occurrence frequency of elements, semantic similarity and the strength of design constraints. Let the co-occurrence number of entity e_i and e_j in the sample set be f_{ij}, the cosine similarity of entity semantic vector be $\mathrm{sim}(e_i, e_j)$, and the matching strength of domain rules be c_{ij}, then the relation confidence score is defined as in this paper

$$s_{ij}^{(k)} = \alpha \frac{f_{ij}}{\max(f)} + \beta\, \mathrm{sim}(e_i, e_j) + \gamma c_{ij}, \quad \alpha + \beta + \gamma = 1 \tag{9}$$

Here, α, β, γ control the contribution of statistical co-occurrence, semantic proximity, and rule constraints, respectively. The reason for this treatment is that it is easy to misjudge the fashion trend as stable knowledge only by high-frequency co-occurrence, and it is possible to ignore the complementary relationship in fashion design only by semantic similarity, while the domain rules can make supplementary constraints on "collocation" and "irreplaceable". It is verified that when $s_{ij}^{(k)} \geq \delta$, the candidate relation is written into the knowledge graph to form a formal edge:

$$A_{ij}^{(k)} = \begin{cases} 1, & s_{ij}^{(k)} \geq \delta \\ 0, & s_{ij}^{(k)} < \delta \end{cases} \tag{10}$$

Here, δ is the relation retention threshold. The function of threshold screening is not only to compress the number of noisy edges, but more importantly to ensure that the relationships in the network have relatively clear design semantics. In the network modeling phase, this paper organizes all valid triples into a multi-relational graph structure

$$\mathcal{G} = (\mathcal{E}, \mathcal{R}, \mathcal{T}) \tag{11}$$

Here, T is the set of all valid triples. For each entity node, the system further aggregates the first-order neighborhood and second-order neighborhood information to form a node representation for subsequent recommendation:

$$h_i^{(l+1)} = \sigma\left(\sum_{r\in\mathcal{R}}\sum_{j\in\mathcal{N}_i^r}\frac{1}{|\mathcal{N}_i^r|}W_r^{(l)}h_j^{(l)}\right) \tag{12}$$

Here, $\mathcal{N}_i^r$ represents the neighbor set of entity ei under relation r, $W_r^{(l)}$ is the relation transformation matrix at the LTH layer, and σ(·) is the nonlinear activation function. This process enables combinatorial knowledge such as "beige -- silk -- wrinkle -- commuting dress", which is not completely determined by a single element, to be continuously encoded through the graph propagation mechanism, rather than stay at the discrete label splicing level. The obtained clothing design element association network not only preserves the explicit relationships between entities, but also converts the implicit dependencies in element collocation into a learnable graph structure. It provides a traceable relationship path for subsequent user preference identification, and also lays a stable structural foundation for scheme generation and combination optimization in the intelligent recommendation stage.

3.4 Clothing design preference identification and user group clustering analysis

In the fashion design recommendation task, user preferences are not directly reflected in the isolated selection of a single item, but more reflected in the continuous response to the combination of several design elements. If only click, collection or purchase records are used to sort the whole, although the surface heat can be obtained, it is difficult to describe the real preference of users for the combination relationship between style outline, comprehensive color, material touch and process details. Based on this, this paper no longer regards user behavior as simple feedback, but maps it into the knowledge graph association rule space, and identifies user aesthetic differences through the rule response structure, and further completes user group clustering. Let the set of high confidence design element association rules extracted from the knowledge graph be

$$\mathcal{R} = \{r_1, r_2, \dots, r_m\} \tag{13}$$

Among them, any rule r_m corresponds to a conditional combination of multiple design elements, such as "beige + silk + crimping + commuting scene" or "dark color + wool blend + stereo cut + urban style". In order to make the rules enter the user modeling process, this paper first constructs the user-rule response matrix

$$Z = [z_{ik}] \in \mathbb{R}^{n\times m} \tag{14}$$

Here, z_{ik} represents the response strength of the user u_i to the rule r_m. If the user produces positive behavior for the sample containing the rule, it indicates that the rule has an activation effect in its preference structure. In this paper, z_{ik} is defined as follows.

$$z_{ik} = \frac{\sum_{j=1}^{N} y_{ij}\ 1(r_k \subseteq T_j)}{\sum_{j=1}^{N} 1\ (r_k \subseteq T_j) + \varepsilon} \tag{15}$$

Here, y_{ij} represents the preference feedback value of user u_i on sample j, T_j represents the set of design elements contained in sample j, 1(·) is the indicator function, and ε is a smoothing term to prevent the denominator from being zero. After this process, each user can be represented by a regular response vector whose high-value dimensions correspond to its more stable design region of interest.

After obtaining the user rule representation, this paper uses the K-means algorithm for unsupervised clustering to identify user groups with similar design preferences. Let the number of clusters be K and user u_i be assigned to cluster centers $\mu_{c(i)}$, then the objective function is

$$J = \sum_{i=1}^{n} \left\| z_i - \mu_{c(i)} \right\|_2^2 \tag{16}$$

This objective is minimized by iteratively updating the user affiliation and cluster center. Since the input space is not the original behavior record, but the structured response of the rule layer, the clustering results no longer only reflect the differences in consumption frequency, but can more clearly distinguish the design tendencies such as "preference for minimalist commuting style", "preference for retro decoration style" or "preference for low saturation and light material combination". As shown in Figure 1, the preference identification process of this paper is expanded from user behavior log, knowledge graph rules, rule activation encoding, user-rule response matrix to clustering output in turn, and finally a preference pattern graph that can serve for recommendation decision is formed.

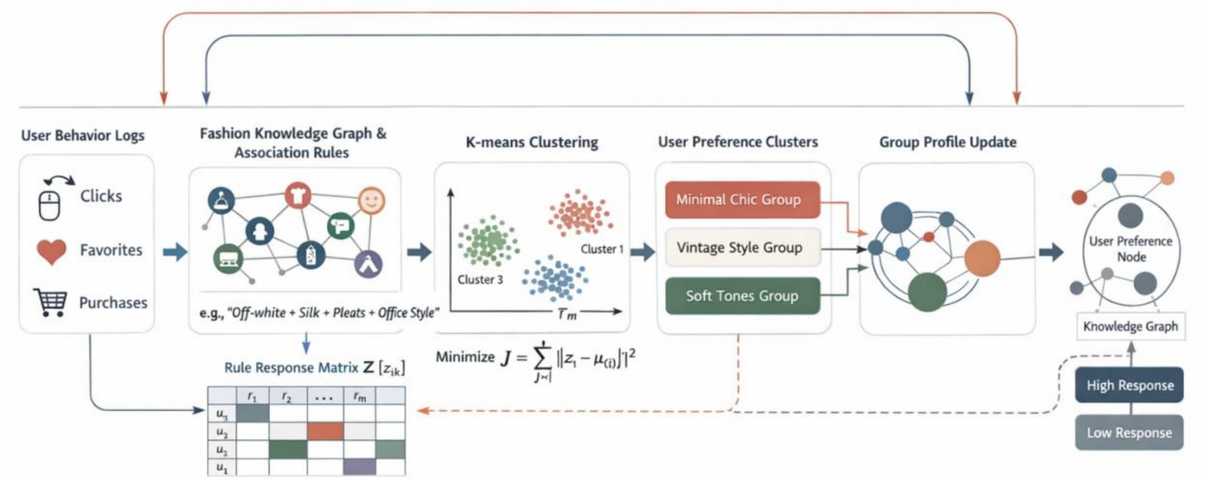

Figure 1: Garment design preference identification and user clustering analysis framework

After the clustering is completed, the system generates a group feature summary for each type of user, counts its high response area and low response area in the rule space, and writes it back to the "user preference" node in the knowledge graph. This means that the user group is no longer just a statistical label outside the recommendation system, but is formally included in the design knowledge network to participate in the subsequent scheme screening and combination optimization. In this way, a closed loop is formed between user preference recognition and graph reasoning: the graph rules provide the structural basis for clustering, and the clustering results in turn modify the preference edge weights in the graph, making the clothing design recommendation more targeted and interpretable.

3.5 Garment design scheme Generation and combination optimization for intelligent recommendation

After extracting the relationship between design elements and clustering user preferences, the core task of the system is no longer to judge whether a certain element is important, but to generate clothing design schemes with combinatorial rationality and aesthetic consistency according to the associated paths in the knowledge graph and the preference structure in the user group. If the recommendation stage still stays at the similar sample retrieval level, the relationship network constructed in the previous section can only play the role of index, and it is difficult to really intervene in the design decision. Based on this, this paper translates high confidence association rules into executable constraint templates, and introduces the graph reasoning results in the process of candidate scheme generation, screening and ranking, forming a scheme combination optimization mechanism for intelligent recommendation. As shown in Figure 2, the mechanism is jointly driven by the knowledge graph relationship path, rule set, user preference portrait and design element space, and outputs the final recommendation results after constraint template construction, candidate scheme generation, consistency filtering and multi-objective scoring.

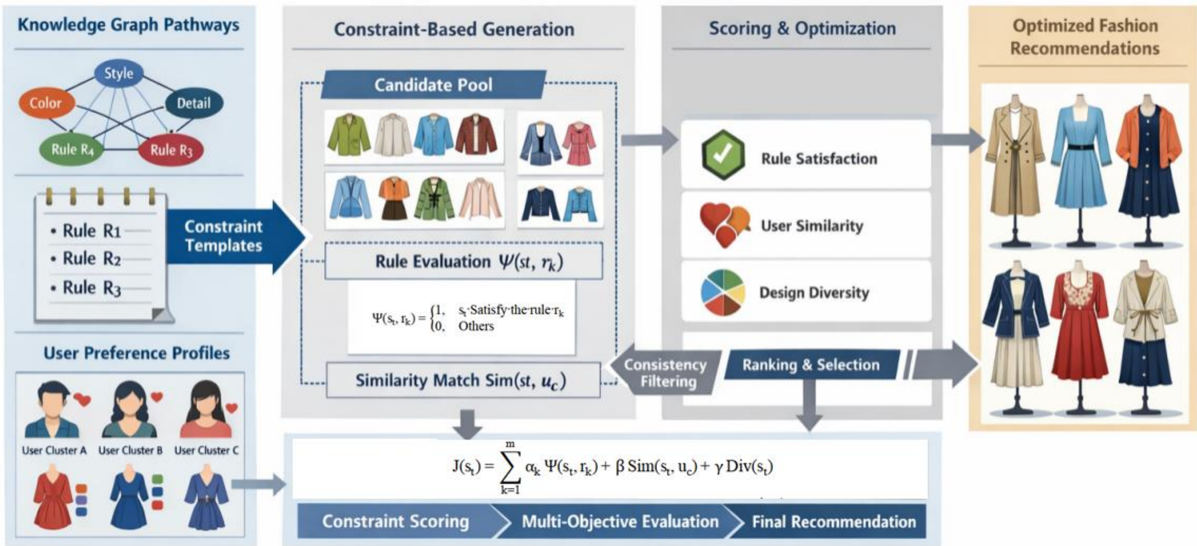

Figure 2: Framework of garment design scheme generation and combinatorial optimization

Let the set of costume design candidates be

$$\mathcal{S} = \{s_1, s_2, \dots, s_T\} \tag{17}$$

Among them, any scheme s_T is composed of elements such as style, color, material and technology. For the set of high-confidence rules from the knowledge graph $\mathcal{R} = \{r_1, r_2, \dots, r_m\}$, this paper defines a response function for each rule

$$\Psi(s_t, r_k) = \begin{cases} 1, & s_t \text{ Satisfy the rule } r_k \\ 0, & \text{Others} \end{cases} \tag{18}$$

This function is used to determine whether the candidate scheme satisfies the element collocation constraint, style consistency and scene adaptation conditions at the same time. Different from unconstrained generation, this approach advances the design knowledge in the graph to the scheme construction stage, so that the generation space is no longer a completely open random combination, but a bounded expansion around interpretable rules. In order to measure the matching degree between the candidate scheme and the target user group, this paper further constructs a multi-objective scoring function:

$$J(s_t) = \sum_{k=1}^{m} \alpha_k \, \Psi(s_t, r_k) + \beta \, \mathrm{Sim}(s_t, u_c) + \gamma \, \mathrm{Div}(s_t) \tag{19}$$

where α_k represents the confidence weight of rule r_k, $\mathrm{Sim}(s_t, u_c)$ represents the similarity between the scheme st and the preference center of user group u_c, $\mathrm{Div}(s_t)$ represents the diversity compensation term of the design scheme on the local element, β and γ are the adjustment parameters. The function does not only pursue the number of rule hits, but also emphasizes the balance between "conforming to preferences" and "avoiding homogenization". If a scheme has high rule satisfaction, but it deviates significantly from the historical preference distribution of the target group, or has excessive repetition in element configuration, the score will still be inhibited.

For the generation implementation, the system does not use an exhaustive search, but extracts candidate combinations from the design element space by layer, and pre-filters them using a consistency threshold:

$$\mathcal{S}' = \{s_t \in \mathcal{S} \mid J(s_t) \geq \tau\} \tag{20}$$

Here, τ is the lowest acceptable score threshold. After filtering, the reserved scheme enters the ranking module, and the optimal recommendation result is finally output:

$$s^* = \arg \max_{s_t \in \mathcal{S}'} J\,(s_t) \tag{21}$$

This processing chain of "rule constraint-score optimization-result output" makes the system not only retain the explicit logic driven by knowledge graph, but also have the ability of dynamic adaptation for user groups. In other words, the recommendation result is not a mechanical reproduction of the existing samples, but a structured new scheme formed by the joint action of design knowledge, preference patterns and combination strategies. This mechanism also provides a unified algorithm entry for satisfaction verification, stability testing and combinatorial distribution analysis in subsequent experiments.

4 Experimental setup and system implementation process

4.1 Construction of garment design element dataset and configuration of experimental environment

In order to verify the effectiveness of the garment design element association network and intelligent recommendation method constructed in this paper, a multi-source heterogeneous data set for garment design tasks is established in the experimental stage. The data mainly comes from the main product map, style detail map, design description text, fabric attribute record, process description document and user interaction log, covering many common categories such as dress, shirt, suit, coat, half skirt, knitwear and so on. After cleaning and deduplicating, a total of 2680 clothing samples were retained, including 2680 groups of image samples, 2680 text descriptions, 2416 material and process attribute records, and 18642 effective user interaction records. In order to ensure the usability of subsequent knowledge graph construction, a unified annotation system is established around the dimensions of style contour, collar type, sleeve type, garment length, main color system, fabric category, process method, applicable season and scene semantics, and all samples are structured annotation and term normalization are completed.

In terms of data division, this paper constructs the training set, validation set and test set according to the ratio of 7:2:1 to avoid sample overlap between model training and effect evaluation. The image side data were uniformly adjusted to 224×224 resolution before entering the model, and background interference reduction, color space conversion and pixel normalization were completed. The text-side data were transformed into standardized description sequences by word segmentation, stop word filtering and term mapping. The material and process fields are further combined with alias and hierarchical compression, so that elements such as "chiffon", "silk blend", "crimp" and "stereo cut" can be encoded into the knowledge graph in a consistent manner. User behavior data comes from clicks, favorites, stay time and explicit ratings. After anonymization, the user behavior data is aligned with the sample entities one by one to form a behavior matrix that can be used for preference identification and recommendation verification.

The system implementation environment uses Python 3.10 as the development language, the knowledge graph construction and relational storage are completed based on Neo4j 5.15, and the graph representation learning and recommendation model training are carried out in the PyTorch 2.1 environment. Clustering and data preprocessing are implemented in Scikit-learn 1.4, Pandas 2.1, and NumPy 1.26. The experimental server was configured with an Intel Xeon Silver 4314 processor, 128 GB memory, and an NVIDIA RTX A6000 graphics card. The above data organization and environment configuration provide a stable experimental basis for subsequent graph training, relational reasoning, user clustering, and design scheme recommendation, and also ensure that the data interface between each module can be consistent.

4.2 Implementation process of knowledge graph training, association reasoning, and recommendation tasks

In the experimental execution stage, we organize the knowledge graph training, association reasoning, and recommendation tasks into a unified process, so as to ensure that the clothing design elements have continuous data semantics from the input graph to the recommendation output, rather than being scattered into independent modules separated from each other. When the system runs, it first reads the clothing image, text description, material process record and user behavior log that have been cleaned and labeled, maps style, color, material, process, scene and user preference into a node set, and generates the initial relationship edges according to the element co-occurrence, text semantics and manual correction rules. After that, the atlas training module updates the entity representation iteratively, so that the similar elements, complementary elements and scene constraints form a more stable structure distribution in the vector space.

In the association inference stage, based on the combination of high-frequency design elements and user positive feedback records, the system filters the scores of "adaptation", "coordination", "complement" and "preference" relations, and retains the relationship paths that meet the threshold conditions to enter the inference library. The purpose of this process is to avoid miswriting accidental co-occurrence as stable knowledge and enhance the expression ability of the graph for clothing collocation logic. After completing the relationship screening, the system continues to perform the user preference mapping task, and converts the user's click, favorite, stay time and rating information on different clothing samples into a rule response vector, and then matches with the user cluster center to form the recommendation trigger conditions for different preference groups. After receiving the portraits of target users or target groups, the recommendation module will dynamically generate candidate solutions from the design element space, filter and rank them according to the graph relationship constraints and preference consistency score, and output the final recommendation results. Table 3 shows the data scale, core operations and parameter configuration of each task link in this stage.

Table 3: Configuration of knowledge graph training, association inference and recommendation task implementation parameters

Stage	Input Object	Sample Size	Core Operation	Main Parameter Settings
Data loading	Images, text, attributes, behavior logs	2,680 samples, 18,642 interactions	Read and align multi-source data	Batch size = 64, loading mode = batch mapping
Knowledge graph training	Entity nodes and initial relation edges	12,436 nodes, 28,715 edges	Entity representation learning and edge weight updating	Epoch = 100, Learning rate = 0.001
Relation filtering	Candidate relation set	9,132 candidate relations	Confidence calculation and redundancy removal	Relation threshold = 0.65, redundancy threshold = 0.12
Preference mapping	User behavior vectors	642 users	Construct rule response matrix and perform clustering	Number of clusters K = 5, maximum iterations = 300
Recommendation generation	User profiles and element space	Dynamic candidate set	Candidate scheme generation, filtering, and ranking	Top-N = 10, consistency threshold = 0.70

5 Analysis of experimental results and evaluation of intelligent recommendation effect

5.1 Effect evaluation index of association network construction of costume design elements

In the evaluation of the construction effect of the association network of clothing design elements, it is often difficult to judge whether the relationship structure really has the power of design interpretation if only the number of nodes and edges in the graph are counted. Based on this consideration, this paper tests the network construction results from four aspects: relation recognition accuracy, relation coverage ability, comprehensive discrimination effect and Average Confidence level. Precision, Recall, F1 and average confidence are used as core indicators respectively. The proposed method is compared with text matching method, image co-occurrence method, fusion feature method and heterogeneous graph neural network method. Each method is run on the same data set and the same set of candidate relations to ensure that the results are comparable.

The experimental results show that the proposed method achieves the optimal performance in the task of garment design element relationship construction. Taking the relationship retention threshold of 0.65 as an example, the proposed method retains 5487 high-confidence edges in 9132 candidate relationships, and the final association network consists of 12436 nodes and 5487 core relationships. Its Precision is 0.873, Recall is 0.841, F1 is 0.857, and the average confidence is 0.812, which are higher than other comparison methods. The Precision of text matching method is 0.736, Recall is 0.707, F1 is 0.721, and the average confidence is 0.694.

The F1 of the image co-occurrence method is 0.748, which indicates that visual co-occurrence alone can capture part of the element collocation law, but its ability to recognize the implicit relationships such as material-craft, style-scene is still limited. The F1 of the fusion feature method is improved to 0.792, which indicates that the multimodal information integration indeed improves the effect of relation judgment. The heterogeneous graph neural network method further improves the F1 to 0.826, but the average confidence is still lower than 0.031 of the proposed method. As shown in Figure 3, the proposed method has the highest F1 value among the five construction strategies, indicating that it achieves a better balance between the accuracy of relation recognition and the coverage ability.

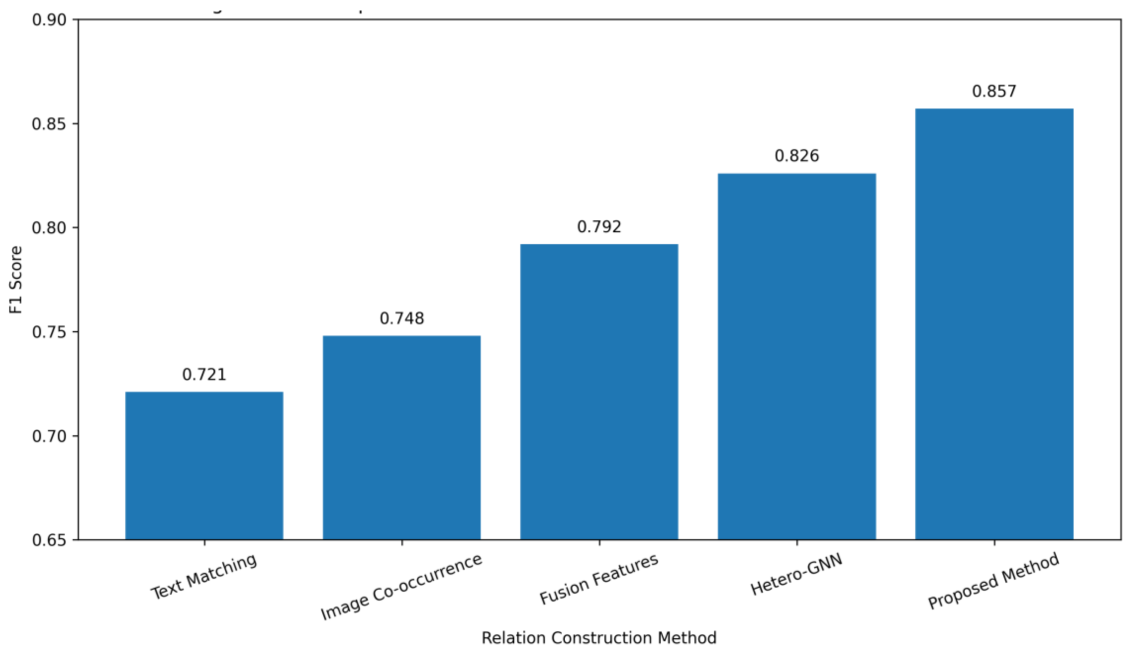

Figure 3: Comparison of F1 values of the methods for constructing association networks of clothing design elements

This result is not only due to the increase of model complexity, but also due to the fact that the explicit semantic relations, user preference feedback and multi-source design labels in the fashion design knowledge graph are incorporated into the relationship screening process, so that "co-occurrence" and "interpretability" are no longer regarded as two separate goals. In contrast, although the text matching and image co-occurrence methods are simple to implement, they are more likely to misjudge the epidemic noise as a stable relationship. Although heterogeneous graph neural networks can enhance structure propagation, they still lack explicit control over the semantic boundaries of the design. On the whole, the proposed method has shown good structural stability and semantic credibility in the construction stage of clothing design element association network, which provides a more reliable relationship basis for subsequent user clustering, intelligent recommendation and scheme optimization.

5.2 Analysis of clustering results of garment design user groups

After constructing the association network of clothing design elements, we further investigate the clustering structure of users in the rule response space to verify whether the preference representation driven by knowledge graph can form a user group with clear boundaries and stable semantics. The K-means method is adopted in the clustering stage. The reason is that the user-rule response matrix generated in the previous section has strong sparsity and discrete combination characteristics, and the centroid division is more conducive to maintaining the interpretability of the group center. In the experiment, the number of clusters K was increased from 3 to 7, and the silhouette coefficient and Davies-Bouldin Index (DBI) were used as the evaluation index. The results show that the proposed method achieves the optimal partition when K=5, the average silhouette coefficient reaches 0.64, and the DBI drops to 0.98, indicating that the consistency of users in the space of preference rules is high within the cluster, and the boundaries between different clusters are clear.

In order to test the influence of different modeling methods on the clustering results, this paper constructs user representations based on text matching, image co-occurrence, fusion feature, heterogeneous graph neural network and the proposed method respectively, and implements clustering under the same parameter conditions. The results show that the contour coefficient of the text matching method is only 0.41 and the DBI is 1.42 under the optimal K=5 condition. 0.45 and 1.36 for image co-occurrence method; The fusion feature method increased to 0.52 and 1.24; Heterogeneous graph neural networks further reach 0.57 and 1.12. In contrast, the silhouette coefficient of the proposed method is 0.23 higher than that of text matching, 0.07 higher than that of heterogeneous graph neural network, and DBI is decreased by 0.44 and 0.14, respectively. As shown in Figure 4, when the number of clusters increased from 3 to 7, the contour coefficient of the proposed method first increased and then decreased, reaching 0.64 when K=5. DBI decreases to 0.98 when K=5, which indicates that the intra-cluster consistency and inter-cluster discrimination achieve a good state at the same time.

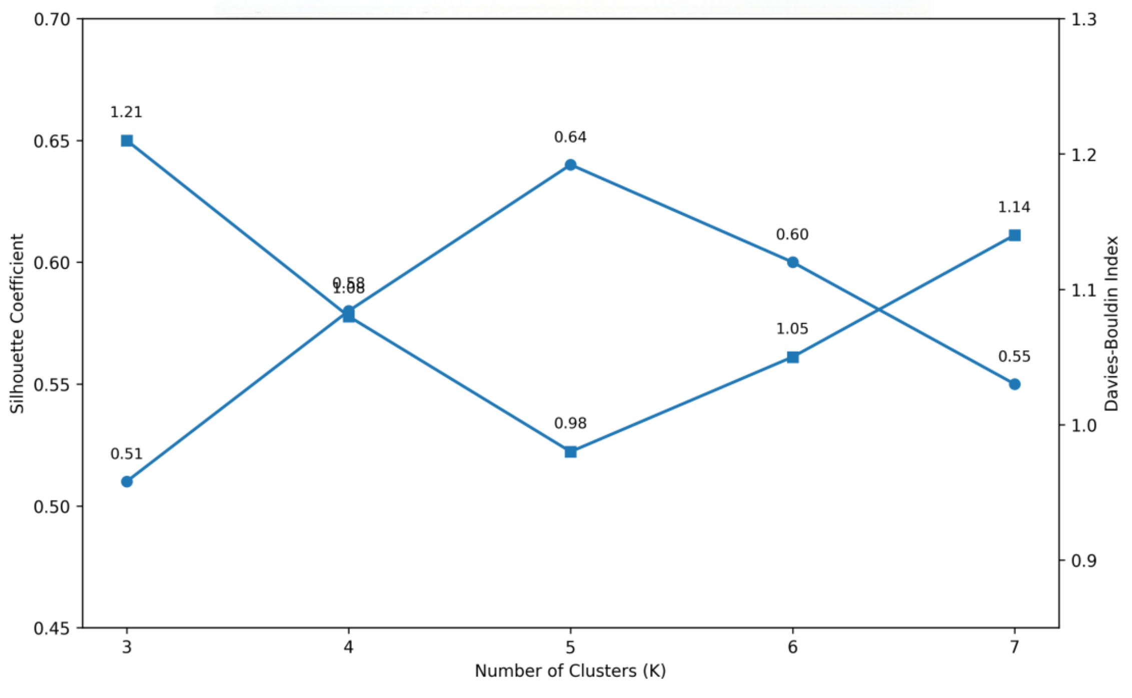

Figure 4: Evaluation of user cluster structure under different number of clusters

From the perspective of clustering semantics, the five user groups roughly correspond to five types of preference patterns: "minimalist basic type", "urban commuting type", "soft light material type", "retro decoration type" and "structure enhancement type". This indicates that the clustering results do not only reflect the differences in consumption activity, but can be mapped to the specific combination tendency of clothing design elements. The reason is that the knowledge graph relationship path and high-confidence association rules are introduced in the user representation stage, so that the behavior data such as click, favorite and rating no longer stays in shallow statistics, but is transformed into a structured response to the combination of style, color, material and process. The resulting user group not only has a more stable boundary, but also provides a more reliable basis for the subsequent recommendation module to design the differentiated scheme according to the group output.

5.3 User satisfaction verification of intelligent recommendation design scheme

In order to test the actual adaptation effect of the recommendation scheme in different user preference groups, this paper constructs a satisfaction verification system based on five types of user clustering, and evaluates it from two dimensions of group response consistency and recommendation acceptance rate. The response consistency is represented by the average cosine similarity of user rating vectors within the same cluster, which measures whether the recommendation results have stable perception within the group. The acceptance rate is expressed as the proportion of users whose satisfaction score is not lower than the threshold 0.75, which reflects the degree to which the recommendation scheme is effectively accepted by the target group. The index system not only measures the explicit acceptance degree of the recommendation results, but also tests the group response stability in similar aesthetic structures.

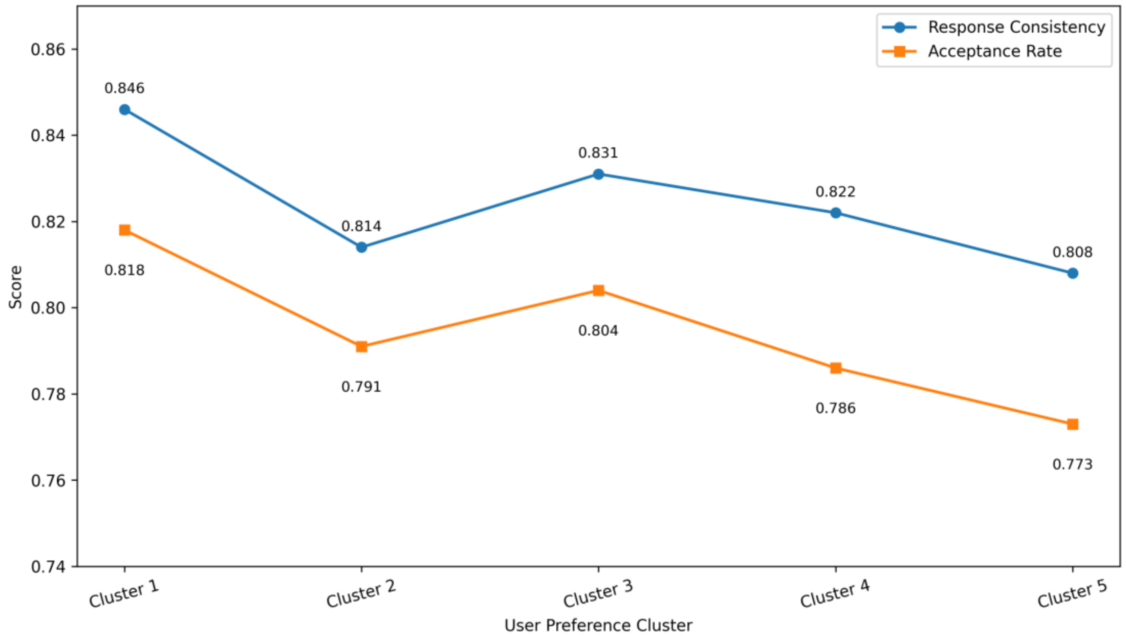

Figure 5: User satisfaction verification of intelligent recommendation design scheme

Experimental results show that the proposed method maintains high satisfaction performance in five user groups. As shown in Figure 5, in terms of response consistency, the scores of Cluster 1 to Cluster 5 are 0.846, 0.814, 0.831, 0.822 and 0.808, respectively, with an average value of 0.824. In terms of acceptance rate, the corresponding results were 0.818, 0.791, 0.804, 0.786 and 0.773, respectively, and the mean value was 0.794. It can be seen that Cluster 1 and Cluster 3 perform particularly well, indicating that for user groups with clear preference boundaries, the knowledge graph driven scheme generation is easier to form a stable response structure. Compared with the comparison methods, the advantages of the proposed method are also obvious. Taking Cluster 1 as an example, the consistency score of the heterogeneous graph neural network method is 0.792, the fusion feature method is 0.756, and the proposed method reaches 0.846. The acceptance rates of the proposed method were 0.744 and 0.713, respectively, which were lower than 0.818 of the proposed method. For Cluster 3, the consistency score of the proposed method is 0.831, which is 0.050 higher than 0.781 of the heterogeneous graph neural network method, and the acceptance rate is increased from 0.729 to 0.804. Even in Cluster 5, where the preference boundary is relatively fuzzy, the consistency of the proposed method is 0.808 and the acceptance rate is 0.773, showing good robustness.

5.4 Comparative analysis of clothing element combination and distribution before and after design optimization

In order to test whether knowledge graph constraints and preference driven optimization really change the structural distribution of recommendation results, this paper further compares the proportion changes of clothing element combinations before and after design optimization. The analysis object is no longer limited to a single style or a single color, but the combination results of contour, color, material and technology are regarded as the overall structural unit, and the problem of whether a certain type of element combination is excessively concentrated and the other combinations are compressed for a long time is investigated. Based on the sample statistical results, this paper selects six representative combinations of clothing elements for comparison, including "neutral color + simple profile", "dark color + structured cut", "light color + soft material", "warm color + decorative process", "natural color + cotton and linen combination" and "cold color + scientific and technological material". As shown in Figure 6, the difference in the proportion of combinations before and after optimization is obvious.

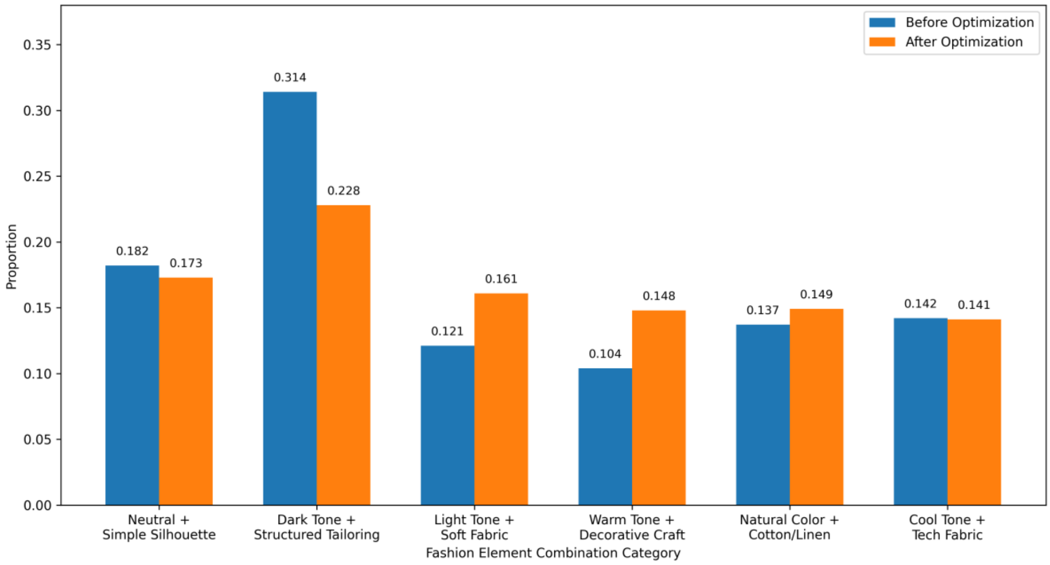

Figure 6: Comparison of clothing element combination distribution before and after design optimization

According to the distribution before optimization, the system output has a strong tendency to concentrate, and the proportion of "dark color + structured tailoring" reaches 0.314, which is significantly higher than that of other combination types. "Warm color + decorative process" is only 0.104, "light color + soft material" is 0.121, indicating that the unoptimized scheme is easier to generate around a few high-frequency safe combinations, resulting in convergence of design style. After the linkage optimization of knowledge graph relationship constraints and user preferences, this phenomenon of single-peak concentration is significantly alleviated. The proportion of "dark color + structured cut" decreased from 0.314 to 0.228, a decrease of 0.086; "Light Tones + Soft Textures" increased from 0.121 to 0.161. "Warm Colors + Decorative

Craft" increased from 0.104 to 0.148; "Natural color + cotton and hemp combination" also increased from 0.137 to 0.149. In contrast, "Neutral Color + simple Profile" was slightly adjusted from 0.182 to 0.173, and "Cool color + Technology Material" remained basically stable from 0.142 to 0.141. It can be seen that the optimization process does not rearrange all combinations evenly, but improves the occurrence probability of the originally underestimated design path while preserving the validity of the mainstream combination.

From the overall structure, the optimized distribution is more balanced. Measured by the range of the proportion of six types of combinations, the difference between the maximum value and the minimum value before optimization is 0.210, and it drops to 0.087 after optimization, indicating that the concentration degree of combination distribution decreases significantly. The reason is that the method in this paper does not directly amplify high-hot elements based on a single historical frequency, but uses the relationships such as "collocation coordination", "material adaptation", "process enhancement" and "scene matching" in the knowledge graph to constrain and re-score the candidate schemes, so that some combinations that were previously ignored due to insufficient sample frequency can re-enter the recommendation space. The resulting results are closer to the generative characteristics of "multi-path coexistence rather than single-path monopoly" in real fashion design, and also provide a more convincing structural basis for the subsequent verification of the model's generalization ability.

5.5 Stability and Generalization testing of recommendation models

In the intelligent recommendation scenario of fashion design, the effectiveness of the model is not only reflected by the hit performance on a single data set, but also depends on whether it can maintain the stability of the relationship structure and the consistency of the recommendation output under the condition of the change of task distribution. To this end, this paper tests the stability of rule structure and the generalization ability of preference output. The former uses the overlap rate of high-confidence rule sets in different task scenarios as the core index to measure the degree of maintenance of knowledge graph relationships in cross-task transfer. The latter is expressed in terms of the output consistency score, which is the average similarity in the element structure of the recommendation schemes received by the same class preference users under different tasks. A total of five types of task scenarios were set up in the experiment, corresponding to commuting clothing recommendation, dress combination recommendation, light outdoor clothing recommendation, simple workplace clothing recommendation and material oriented design recommendation. An independent test subset and non-overlapping user samples were used for each task to avoid data interference between scenarios.

The experimental results show that the rule overlap rates of the proposed method in the five tasks are 0.806, 0.791, 0.784, 0.798 and 0.812, respectively, and the average is 0.798. The output consistency scores were 0.783, 0.801, 0.792, 0.806 and 0.815, respectively, and the average value was 0.799. As shown in Figure7, both indicators remain above 0.78 under the five types of tasks, and the fluctuation range is small, which indicates that there is no obvious structural instability in the model during the task transfer process. Among them, Task 5 has the best performance, with the rule overlap rate reaching 0.812 and the output consistency reaching 0.815, indicating that the knowledge graph has a more prominent constraint effect on the recommended path in the design task with a more clear material-process relationship. The rule overlap rate of Task 3 is the lowest, which is 0.784, but it is still higher than the average level of the comparison methods, indicating that even in tasks with relatively flexible style boundaries such as light outdoor, the model can still maintain good knowledge transfer ability.

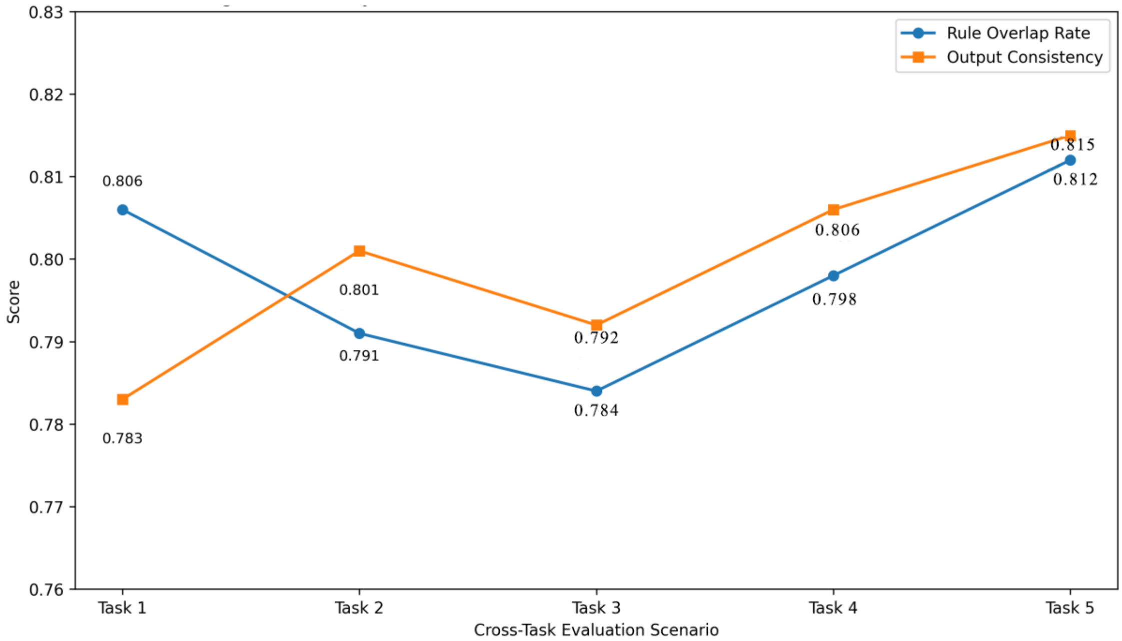

Figure 7: Recommendation model stability and generalization ability test

Compared with the comparison methods, the advantages of the proposed method are also obvious. Calculated by the average of five tasks, the rule overlap rate of the heterogeneous graph neural network method is 0.736, the fusion feature method is 0.701, and the text matching method is only 0.652. In terms of output consistency, the corresponding results are 0.744, 0.713 and 0.668, respectively. In other words, compared with the heterogeneous graph neural network, fusion feature and text matching methods, the proposed method improves the rule overlap rate by 0.062, 0.097 and 0.146, and improves the output consistency by 0.055, 0.086 and 0.131, respectively. The reason for this difference is that the proposed method does not only rely on local feature contributions for ranking, but puts knowledge graph relationship paths, user preference rules and scheme generation constraints into the same computational framework, so that the recommendation model can still maintain strong structural continuity when tasks change. On the whole, the proposed model shows good stability and generalization ability in cross-scene fashion design tasks, indicating that it is not only suitable for a single recommendation environment, but also has the potential to be extended to more complex design tasks.

6 Discussion

From the experimental results, the advantages of the proposed method are not only reflected in the improvement of a single index. Through multi-source data collection, label generation, relationship extraction, user preference clustering and scheme combination optimization, a complete calculation chain from design knowledge organization to recommendation output is formed. Traditional methods often focus on image similarity or attribute co-occurrence, which can identify local collocation rules, but it is difficult to explain why the stable association between style, color, material and technology is formed. In this paper, we explicitly organize design knowledge through knowledge graph, and then incorporate high-confidence relationships and user preference responses into the modeling process, so that the association network not only has structural integrity, but also has certain design interpretation power. User clustering results show that the rule response space is more suitable for describing aesthetic differences than the original behavior space, which indicates that clothing preference is not a direct projection of a single click behavior, but a comprehensive reflection of multiple design elements in user cognition. After introducing the constraint generation mechanism in the recommendation stage, the output schemes are improved in terms of group consistency, acceptance rate and cross-task stability, which indicates that the knowledge graph does not stay at the static storage level, but really participates in the selection and optimization of schemes. It should also be noted that the proposed method still relies on high-quality label system and relation initialization, and the effect of graph inference will still be affected if the original data is seriously missing or semantic drift. This also suggests that subsequent research needs to further enhance the ability of automatic annotation and dynamic update.

7 Conclusions

Focusing on the problems of scattered relationships between clothing design elements, difficulty in structured expression of user preferences, and insufficient interpretation of recommendation results, this paper proposes a knowledge graph based clothing design element association network construction and intelligent recommendation method. The design, color, material, process and scene semantics are integrated into the unified graph structure. Through multi-source data collection, label generation, relationship extraction, user preference clustering and scheme combination optimization, a complete calculation chain from design knowledge organization to recommendation output is formed. The experimental results show that the F1 value of the proposed method in the association network construction reaches 0.857, the optimal contour coefficient in the user clustering stage is 0.64, and the average acceptance rate of the recommendation scheme in different preference groups reaches 0.794. The rule overlap rate and output consistency in cross-task testing also maintain a high level. This shows that the knowledge graph can not only improve the integrity of the relationship expression of clothing design elements, but also enhance the stability and interpretability of the recommendation results. It should be pointed out that the proposed method still relies on the quality of labels and the initial relationship construction, and there is still room for improvement in the ability of graph update and generation when facing more complex open design semantics. In the future, richer multi-modal data and generative models can be combined to further expand the scope of adaptation and design innovation ability of recommender systems.

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