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Empirical Study on the Pathways for Enhancing Product Value Through Industrial Design Innovation in the Context of Smart Manufacturing

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SUMMARY: *In the context of intelligent manufacturing, this paper proposes a modeling framework for product value enhancement path driven by industrial design innovation. Based on 1536 product design samples and 18240 innovation behavior records, a multi-modal feature matrix covering morphological and semantic structure, functional configuration, process parameters, user interaction feedback and market response is constructed. Product value labels are generated through innovation execution scores, manufacturing adaptation scores, and feedback acceptance scores. The interpretable value improvement paths were extracted by combining graph association analysis and rule learning, and the path rules were retained under the support threshold of 0.08 and the confidence threshold of 0.67. The rule vectors are clustered into five product innovation patterns with a silhouette coefficient of 0.66. The path with high confidence is embedded into the intelligent design generation module as a constraint control condition. The experimental results achieve 91.4% path recognition accuracy and 88.7% value response consistency, which verifies the effectiveness and cross-scene adaptability of the proposed framework.*

KEYWORDS: *Ntelligent manufacturing; Industrial design innovation; Product value enhancement; Graph association learning*

1 Introduction

The intelligent manufacturing environment is reconstructing the product development chain, and the role of industrial design extends from modeling to value identification, requirement mapping, scheme generation and manufacturing collaboration. Existing researches on product value enhancement mainly focus on design evaluation, user response or production performance analysis. There is still a lack of unified data expression and structural connection among industrial design innovation behavior, manufacturing process status and value results. This paper focuses on the mechanism of industrial design innovation to promote product value improvement, and forms three research judgments: multi-source design feature coding can enhance the consistency of product value representation, graph association and rule learning can refine interpretable value transmission structure, and path constraint embedding generation mechanism can output design schemes that are more suitable for manufacturing context and user feedback.

Vlah et al. [1] reviewed the research evolution of data-driven engineering design. Wang et al. [2] discussed the logic of extending data-driven product design to intelligent stage. Wu et al. [3] proposed a customer requirements mining method driven by semantic analysis. Tsunetomo et al. [4] studied the design process of intelligent product service system. Cong et

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al. [5] used self-organizing maps to carry out user-centric conceptual design. Yuksel et al. [6] reviewed the application of artificial intelligence in engineering design. Zhang et al. [7] summarized the research context of human-centered intelligent manufacturing. Demirel et al. [8] proposed a human-centered generative design framework supporting concept generation and evaluation. Liu et al. [9] discuss how data science and product design can be integrated. Soori et al. [10] reviewed the application of digital twin in intelligent manufacturing.

The existing achievements cover requirements analysis, generative design, product service system and digital twin, but the value increases formed by design innovation activities in different manufacturing stages are still mostly dependent on discrete indicators, and the path expression in the same logical space among design semantics, process constraints, user interaction and market feedback has not yet formed. Industrial design innovation is not a single stage of creative output, but a continuous calculation process throughout product definition, structural configuration, manufacturing adaptation and value response. Only when design behavior, manufacturing data and value feedback are incorporated into the unified representation space, a more stable mapping relationship can be established between the sample layer, the rule layer and the pattern layer.

Based on the above understanding, this paper regards industrial design innovation as a computable, learnable, and verifiable dynamic behavior set, and constructs a product value improvement path modeling framework for intelligent manufacturing scenarios. The research organizes design attributes, innovation behavior, process status and feedback results through multi-source feature coding, completes value representation through label generation, identifies value transmission paths through graph association and rule learning, and then uses sample clustering to extract typical value improvement patterns, and empathes high confidence paths into the intelligent generation of design schemes. It forms a complete technical chain from data organization, path identification to value response verification. This study is helpful to promote the industrial design from result evaluation to process calculation and rule verification, and also provides a reusable computing framework for product value enhancement in intelligent manufacturing environment.

2 Related work

Existing research mainly focuses on the construction of intelligent manufacturing system, data-driven design, user requirements modeling and generative design. However, the research on organizing industrial design innovation behavior, manufacturing process state and product value increment as unified computing links still needs to be further refined. Peruzzini et al. [11] studied the design framework of intelligent manufacturing system oriented to Industry 5.0, and incorporated human-machine collaboration, system integration and manufacturing organization into the unified modeling perspective. Ordek et al. [12] reviewed the main technical paths of machine learning to support manufacturing, and summarized the application scope of prediction, classification, optimization and decision aid in manufacturing scenarios. Gao et al. [13] studied the application status of artificial intelligence in manufacturing and proposed that manufacturing intelligence is shifting from single-point recognition to cross-link collaborative reasoning. Renard et al. [14] studied the iterative modeling method from sensors to digital twins, and showed that a continuous data closed loop can be formed between physical devices, state perception and virtual mapping.

Wang H et al. [15] proposed an autonomous intelligent manufacturing system driven by data and knowledge, which combines knowledge rules, state cognition and plant-level autonomous control. Ren et al. [16] reviewed and looked forward to the development direction of Smart product-service Systems 2.0, and put Product function, Service logic and value co-creation relationship into a unified discussion framework. Zhang Y et al. [17] studied the modeling and evolution analysis method of user requirements based on comment data, which provided data support for product attribute upgrading. Wang X et al. [18] proposed a machine learning algorithm for user experience improvement in product design, which linked user response characteristics with design decision results.

Wu Y et al. [19] constructed a product upgrade method that integrated QFD and FMEA, so that requirement mapping, failure analysis and upgrade decision could be carried out in the same framework. Wang Z et al. [20] studied the mining method of user requirements for product design based on online reviews and Kano model, which enhanced the connection strength between requirement identification and design expression. Jiang et al. [21] studied the data-driven generative design method for mass customization, and verified the feasibility of coupling between design generation and personalized configuration through case analysis. Abdel-Aty et al. [22] reviewed the concept construction of digital thread in intelligent manufacturing, and showed that data objects in design, process, production and service stages can be continuously associated in a unified thread. Wang Y et al. [23] proposed an ecological design ontology model for additive manufacturing, and constructed a design knowledge expression mechanism combined with sustainability analysis.

The existing works mainly focus on requirements identification, experience evaluation, service integration and manufacturing autonomy, but lack of empirical description of the conduction mechanism of industrial design innovation in scheme definition, structure configuration, process adaptation and feedback, and rarely incorporate rule learning, pattern recognition and value enhancement output into the same computational closed loop. This makes the product value improvement stay more at the discrete index comparison level, and there is still room for compression of the logical connection between cross-stage data organization, path expression and result generation. Based on the above research results, this paper constructs multi-source feature coding, value label generation, graph association path mining, sample group clustering and scheme intelligent generation mechanisms, which are used to identify the calculation path of industrial design innovation driven product value improvement, and provide a unified modeling basis for subsequent experimental verification. These researches provide the methodological foundation for the system architecture design, requirement mapping organization, knowledge representation modeling and generation constraint setting, and also make the interpretable modeling of product value enhancement path have a clearer technical direction. At the same time, the collaborative calculation between design innovation and manufacturing response obtains clearer empirical support.

3 Modeling method of industrial design innovation and product value enhancement path

3.1 Construction of multi-source feature codes for product design for intelligent manufacturing scenarios

The identification of product value improvement path depends on the unified expression of design information, manufacturing information and feedback information. In order to enable the industrial design innovation behavior in the intelligent manufacturing environment to enter the subsequent path mining process, this paper constructs a multi-source joint coding framework to standardize the form semantics, functional configuration, process adaptation, feedback response and scene context of product samples. Design attributes, manufacturing status and value feedback are integrated into the same data structure, so that the transmission relationship of design innovation in product definition, process execution and value formation can be continuously described.

In the morphological semantic coding, the structural representation is extracted according to the component contour, surface change, hierarchical relationship and connection mode, and the difference relationship between local adjacent units is used to measure the design coupling strength.

$$S_i = \frac{1}{|\mathcal{N}(i)|} \sum_{j \in \mathcal{N}(i)} \omega_{ij} \exp\left(-\|p_i - p_j\|_2\right) \tag{1}$$

where S_i represents the local structural coupling strength of the i design unit, $\mathcal{N}(i)$ represents the set of design units adjacent to the unit,$|\mathcal{N}(i)|$ represents the number of adjacent units, ω_{ij} represents the connection weight between unit i and unit j, p_i and p_j represent the parameter representation vector of the corresponding unit. $\|p_i - p_j\|_2$ denotes the Euclidean distance between the two in the parameter space. The formula is used to describe the organization closeness between the local morphological units of the product, and the structural adjacency relationship and parameter difference are incorporated into the encoding process at the same time, so as to reflect the expression strength of the industrial design scheme at the structural level more accurately.

In the process adaptation part, manufacturing execution information is further introduced to uniformly normalize machining accuracy, material matching, assembly stability and process continuity, so that design-side features and manufacturing-side states are consistent in the same computational space.

$$M_c = \frac{1}{T} \sum_{t=1}^{T} (\alpha_1 q_t + \alpha_2 r_t + \alpha_3 u_t) \tag{2}$$

Here, M_c represents the process adaptation score of the product sample, T represents the number of processes in the manufacturing process, q_t represents the dimensional accuracy score of the t process, r_t represents the material matching score corresponding to the process, u_t represents the assembly stability score, and α_1, α_2 and α_3 represent the weight coefficients of the three subterms. The formula is used to comprehensively describe the overall matching degree between the design scheme and the manufacturing process, so that the design innovation does not stop at the modeling level, but can enter the value modeling process in which the manufacturing constraints and execution conditions are jointly involved.

Table 1 presents the structural composition of the multi-source feature coding, which is used to illustrate the standardized organization way of product design samples in the smart manufacturing environment.

Table 1: Product design multi-source feature coding structure

Feature Category	Feature Content	Representation Method	Encoding Dimension
Morphological Semantic Features	Component contours, surface curvature variation, structural hierarchical relationships	Continuous vectors	24
Functional Configuration Features	Module combination strength, interface coupling degree, functional coverage	Discrete encoding and frequency mapping	18
Process Adaptation Features	Processing precision, material compatibility, assembly stability	Continuous normalized data	12
Feedback Response Features	Click retention rate, solution adoption rate, after-sales consistency	Continuous score vectors	10
Scene Context Features	Product category, manufacturing batch, application scenario labels	Categorical embedding representation	8

After coding all kinds of information, all samples are concatenated into a unified product representation in a fixed order, and the value expression form is constructed.

$$V_p = \beta_1 G_s + \beta_2 F_m + \beta_3 M_c + \beta_4 R_f \tag{3}$$

Among them, V_p represents the basic value expression result of a single product sample, G_s represents the morphological and semantic score, F_m represents the functional configuration score, M_c represents the process adaptation score, R_f represents the feedback response score, and β_1 to β_4 represents the weight of each dimension feature in the value expression. The function of this formula is to compress design expression, function organization, process adaptation and feedback response into the same value representation space, which provides a unified numerical basis for subsequent product value label generation and path mining.

Finally, all the samples form a standardized feature matrix, which is used as a unified data interface for subsequent value label generation, graph association path mining and group pattern recognition. After this processing, the data from heterogeneous sources are organized into the same computing framework, which not only retains the multi-dimensional attributes of industrial design innovation at the form, function and process levels, but also establishes a stable connection relationship among design side, manufacturing side and feedback side.

3.2 Industrial design innovation behavior data and product value label generation

Industrial design innovation behavior data are used to construct product value labels. In this paper, design iteration frequency, scheme adoption rate, manufacturing correction times, interactive feedback intensity and market response increment are organized as behavioral data matrix, so that a unified mapping can be established among design execution, manufacturing adaptation and value feedback. In order to weaken the influence of the differences of different index dimensions on subsequent path learning, the behavioral data of each dimension are standardized independently, and the calculation formula is as follows.

$$\hat{b}_{ij} = \frac{b_{ij} - b_j^{min}}{b_j^{max} - b_j^{min}} \tag{4}$$

Here, $\hat{b}_{ij}$ represents the standardized result of the i sample on the j behavior dimension, b_{ij} represents the corresponding original behavior value, and b_j^{max} and b_j^{min} represent the maximum and minimum value of the j behavior in all samples, respectively. The formula is used to compress the heterogeneous behavior signals into a uniform numerical interval, which ensures that the design innovation activities, manufacturing execution status and feedback results remain comparable at the same scale.

After standardization, this paper uses weighted fusion to generate continuous value response scores, and compresses the three types of signals of innovation execution, manufacturing adaptation and feedback acceptance into a single label basis, which is calculated as follows.

$$y_i = \lambda_1\hat{d}_i + \lambda_2\widehat{m}_i + \lambda_3\hat{f}_i, \lambda_1 + \lambda_2 + \lambda_3 = 1 \tag{5}$$

Here, y_i represents the comprehensive value response score of the i sample, $\hat{d}_i$ represents the design innovation execution score, $\widehat{m}_i$ represents the manufacturing adaptation score, $\hat{f}_i$ represents the feedback acceptance score, and λ_1, λ_2, and λ_3 represent the weight coefficients of the three types of signals in the comprehensive score. This formulation is used to transform discrete behavioral data into continuous value representations, so that the label generation process not only retains the dynamic differences of design activities, but also reflects the joint effect of manufacturing constraints and external feedback on value formation.

Table 2 presents the mapping form of innovation behavior data and value score for industrial design. The table shows the standardized results of the sample in the three dimensions of innovation execution, manufacturing adaptation and feedback acceptance and their corresponding comprehensive scores, which are used to illustrate the way of data organization before the generation of value labels.

Table 2: Industrial design innovation behavior and value score mapping

Sample ID	Innovation Execution Score	Manufacturing Adaptation Score	Feedback Acceptance Score	Comprehensive Value Score
P01	0.81	0.76	0.73	0.770
P02	0.64	0.69	0.66	0.665
P03	0.88	0.82	0.79	0.830
P04	0.71	0.74	0.68	0.711

After the standardization and weighted fusion of the behavior values in Table 2, a clearer value distinction boundary is formed. In order to ensure that the subsequent graph association learning and rule mining have a clear discrimination basis, this paper sets a unified value threshold and converts the continuous score into a binary label, which is calculated as follows.

$$z_i = \begin{cases} 1, & y_i \geq \theta \\ 0, & y_i < \theta \end{cases} \tag{6}$$

Here, z_i represents the discrete value label of the i sample, θ represents the global value discrimination threshold, and y_i represents the comprehensive value response score of the corresponding sample. When the comprehensive score is not lower than the threshold, the sample is classified into the high-value interval. When the comprehensive score is below the threshold, it is classified into the common value interval. This formula is used to complete the value label discretization, so that a one-to-one correspondence supervision relationship can be formed between behavior data, design features and value results.

After label generation, the discrete value labels will be aligned sample by sample with the multi-source feature encoding constructed in the previous section to further form a unified training dataset. After this treatment, industrial design innovation behaviors are no longer just scattered records, but are transformed into value representation results with clear boundaries. This not only enhances the semantic connection between behavior signals and product value, but also provides a stable data basis for subsequent value improvement path mining, group pattern recognition and intelligent scheme generation, so that the whole modeling link has better structural consistency and computational traceability at the input end.

3.3 Value improvement Path Mining based on Graph Association and rule learning

Product value improvement path mining takes the multi-source feature coding results and value label results as input, and aims to extract stable path association patterns among industrial design innovation, manufacturing execution constraints and value response. After the samples have been uniformly coded, morphological semantics, functional configuration, process adaptation and feedback response are organized into structured attribute sets. In order to meet the input requirements of subsequent rule learning, the continuous features are discretized, and the numerical information from different sources is converted into a composable set of attribute items through semantic mapping. The transaction structure formed in this way not only retains the stage differences of design innovation activities, but also enables the key clues in the value formation process to enter the same rule space, which provides a standardized data interface for the subsequent path rule screening and graph association calculation.

In the graph correlation modeling stage, design units, manufacturing constraints and feedback signals are represented as heterogeneous nodes, and edge weights are constructed based on co-occurrence frequency and semantic coupling relationship. The correlation strength between any two types of nodes in the graph is defined as follows.

$$A_{uv} = \eta \frac{n_{uv}}{\sum_k n_{uk}} + (1 - \eta) P(v|u) \tag{7}$$

where A_{uv} represents the association strength between node u and node v, n_{uv} represents the co-occurrence number of them in the sample, $\sum_k n_{uk}$ represents the total occurrence number of node u and all adjacent nodes, $P(v|u)$ represents the conditional probability, η represents the balance coefficient between the frequency term and the condition term. This formulation is used to build the initial graph structure of the value path.

After completing the graph structure organization, this paper extracts candidate path itemsets from the subset of high-value samples and filters frequent patterns according to their support. Support is defined as follows.

$$\mathrm{supp}(P) = \frac{1}{|D^+|} \sum_{x \in D^+} 1\,(P \subseteq T_x) \tag{8}$$

Here, $\mathrm{supp(P)}$ represents the support of candidate path itemset P, $\mathrm{D^+}$ represents the set of high-value samples, $\mathrm{T_x}$ represents the transaction itemset corresponding to sample x, and $1(\cdot)$ represents the indicative function. This formula is used to identify the value enhancement patterns with repeated characteristics and eliminate the low-frequency paths with strong randomness.

On this basis, this paper further constructs conditional rules to describe the possibility of a certain type of design innovation activity producing high-value results under the constraints of manufacturing conditions. The rule confidence is defined as follows.

$$\mathrm{conf(P \Rightarrow z = 1)} = \frac{\mathrm{supp(P \cup \{z = 1\})}}{\mathrm{supp(P)}} \tag{9}$$

Here, $\mathrm{conf(P \Rightarrow z = 1)}$ represents the confidence that a path rule points to a high-value outcome, P represents a rule antecedent, and $\mathrm{z = 1}$ represents a high-value label event. This formulation is used to retain candidate rules with strong explanatory power.

Considering that the path itemset will grow rapidly during expansion, we further introduce a comprehensive scoring function under graph constraints to jointly rank support, confidence and structural closeness, which is of the form:

$$\mathrm{score(P)} = \mu_1 \mathrm{supp(P)} + \mu_2 \mathrm{conf(P \Rightarrow z = 1)} + \mu_3 \frac{1}{|\mathrm{E_P}|} \sum_{\mathrm{(u,v) \in E_P}} \mathrm{A_{uv}} \tag{10}$$

where $\mathrm{score(P)}$ represents the comprehensive score of path P, μ_1, μ_2 and μ_3 represent the weights of the three types of indicators, $\mathrm{E_P}$ represents the set of internal edges of the path, and $\frac{1}{|\mathrm{E_P}|}\sum \mathrm{A_{uv}}$ represents the average connection strength of the path in the heterogeneous graph. This formulation is used to complete the final screening of candidate paths.

After the above processing, the potential connections among industrial design innovation behavior, manufacturing execution state and value response results are organized as a computable set of path rules, which can not only be used as the input of subsequent group pattern recognition, but also provide a constraint basis for intelligent scheme generation. At the same time, it ensures that the path output has better structural traceability.

3.4 Product value enhancement pattern recognition and sample group clustering

In order to realize the structural identification of product value improvement paths at the sample group level, this paper vectorizes the high confidence path rules, and constructs the sample-rule response matrix as the clustering basis. Each path rule corresponds to a set of design innovation attributes, manufacturing constraint attributes, and value outcome attributes. The rule is encoded into a uniform binary indicator vector after discrete mapping. A value of 1 means that the corresponding attribute item is activated by the path, and a value of 0 means that the attribute is not included. After all the rules are encoded, a rule representation matrix can be formed, which is used to maintain the consistent expression of path structure in the uniform attribute space. Based on this matrix, the subsequent sample response calculation is carried out around the path hitting situation, so as to ensure that the pattern recognition process has a clear structural boundary and strong interpretability.

In the rule response modeling phase, this paper defines the activation strength of a sample to a single path rule as follows.

$$g_{ik} = \frac{1}{|P_k|} \sum_{a \in P_k} 1\,(a \in T_i) \tag{11}$$

Here, g_{ik} represents the activation strength of the i sample to the k path rule, P_k represents the set of attribute items contained in the k path rule, $|P_k|$ represents the number of attribute items of the rule, and T_i represents the set of transactions corresponding to the i sample. The formula is used to measure the proportion of the sample satisfying the rule, and the sample-rule response matrix is generated.

Algorithm is used to complete path rule vectorization and sample screening. The input is the set of high confidence value improvement paths, discrete attribute space and candidate product sample set, and the output is the effective sample set and rule activation matrix. The algorithm first generates attribute indicator vector for each path rule, and then calculates its satisfaction for each path sample by sample. When a sample triggers at least one high-value path, the sample is retained in the valid set. After this process, the original samples are projected to the regular subspace, and the response differences of design innovation activities under different manufacturing conditions can also enter the subsequent clustering analysis in a unified form.

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Algorithm: Vectorization of path rules and sample screening
Input: set of high confidence paths, discrete attribute space, set of candidate samples
Output: valid sample set, rule activation matrix
Step 1: Initialize the rule activation matrix
Step 2: Iterate over each path rule and generate the attribute indicator vector
Step 3: Iterate over each sample and calculate its activation result for all path rules
Step 4: Keep samples that trigger at least one high-value path
Step 5: Return the set of valid samples and the rule activation matrix
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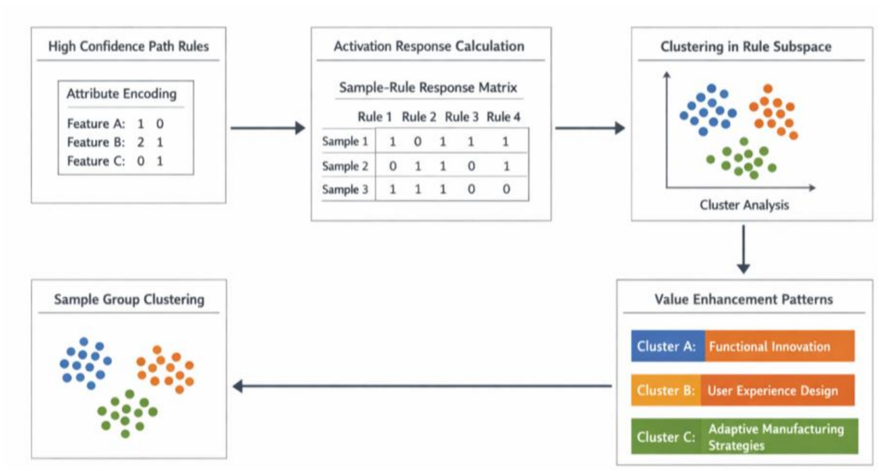
Fig. 1 illustrates the pattern recognition process based on path rule vectorization and sample population clustering. In the figure, the high confidence path is encoded by attributes, and then the activation response of the sample to the rule is calculated. Then the sample-rule response matrix is formed, and the clustering group is completed in the rule subspace, and finally the value improvement pattern graph is obtained. The graph can reflect the degree of agreement in path response within the group, and can also show the structural differences in design innovation methods and manufacturing adaptation strategies between different groups.



	Rule 1	Rule 2	Rule 3	Rule 4	
Sample 1	1	0	1	1	1
Sample 2	0	1	1	0	1
Sample 3	1	1	1	0	0

Figure 1: Pattern recognition process based on path rule vectorization and sample population clustering

After obtaining the sample-rule response matrix, this paper uses the K-means algorithm to perform unsupervised clustering of the samples, and its objective function is defined as follows.

$$J = \sum_{i=1}^{n} \sum_{c=1}^{K} \delta_{ic} \|g_i - \mu_c\|_2^2 \tag{12}$$

Here, J represents the clustering objective function, n represents the number of samples, K represents the number of clusters, δ_{ic} represents whether sample i is assigned to the c cluster, g_i represents the rule response vector of sample i, μ_c represents the c cluster center, and $\|\cdot\|_2^2$ represents the squared Euclidean distance. This formula is used to minimize the deviation of rule response within the group, so that the samples of the same class can maintain high consistency in the structure of value enhancement path.

After the above processing, the high confidence path rules are further transformed from discrete attribute combinations into a structured pattern space that can be clustered and compared. The sample group thus obtained is not just a simple classification result, but a centralized expression of the relationship between industrial design innovation, manufacturing execution constraints and value response. The pattern set can not only provide a constraint basis for subsequent value enhancement scheme generation, but also provide a stable input for group difference analysis and response consistency evaluation, so that the product value improvement path can obtain a clearer calculation expression at the sample level.

3.5 Intelligent generation mechanism of design innovation scheme for product value enhancement

After the value improvement path mining and sample group identification are completed, an intelligent generation mechanism of design innovation schemes with constraint control ability should be constructed to ensure that the output schemes are consistent with the path rules in the three levels of design attributes, manufacturing adaptation and value response. The mechanism transforms path rules into computable combinatorial constraints, and performs feasibility screening, response scoring and ranking output in the candidate solution space, so that the scheme generation process maintains clear logical boundaries and traceability. Fig. 2 illustrates the process of design innovation scheme generation driven by the value enhancement path.

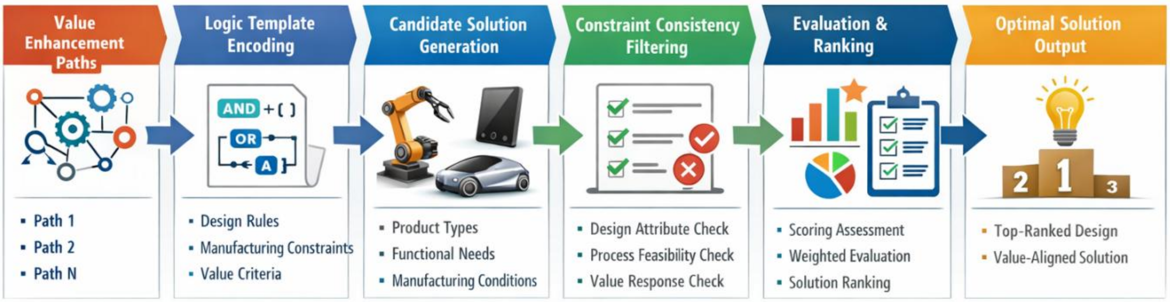


Figure 2: Value enhancement path-driven design innovation scheme generation process

As shown in Fig. 2, the set of value enhancement paths is first encoded as a logical template, and then the set of candidate solutions is generated according to product categories, functional requirements and manufacturing conditions. After the candidate scheme enters the constraint consistency calculation module, the system judges whether it satisfies the design attributes, process constraints and feedback structure in the path rules one by one. When the satisfaction degree of a single scheme to a single path rule needs to be calculated, the following response function is used.

$$\Psi(s_t, p_k) = \frac{1}{|p_k|} \sum_{a \in p_k} 1\,(a \in s_t) \tag{13}$$

Here, $\Psi(s_t, p_k)$ represents the response value of candidate scheme s_t to path rule p_k, $|p_k|$ represents the number of attribute items included in the path rule, a represents a single attribute item in the path, and $1(a \in s_t)$ represents whether the attribute item is activated by the current scheme. This formula is used to characterize the degree of local agreement between the candidate alternatives and the value path.

After the local response value is calculated, the system further constructs a feasible alternative screening condition to only retain the design results with sufficient response strength for the rule set, which is defined as follows.

$$S_f = \left\{ s_t \in S \mid \sum_{k=1}^{m} \Psi\,(s_t, p_k) \geq \tau \right\} \tag{14}$$

Here, S_f represents the set of feasible alternatives after constraint screening, S represents the original candidate alternative space, m represents the number of path rules involved in the screening, and τ represents the minimum response threshold that the alternative needs to reach to the next stage. The formula is used to eliminate the schemes with inconsistent structure, so that the subsequent ranking is based on the stability constraint.

After consistency screening, the feasible scheme is jointly scored by the system's comprehensive design innovation intensity, manufacturing adaptation level and value expected benefit, which is in the form of:

$$J(s_t) = \rho_1 D_t + \rho_2 M_t + \rho_3 V_t \tag{15}$$

where $J(s_t)$ represents the comprehensive score of the candidate scheme s_t, D_t represents the design innovation intensity, M_t represents the manufacturing adaptation level, V_t represents the expected benefit of value, and ρ_1, ρ_2 and ρ_3 represent the weight coefficients of the three evaluation dimensions. The formula is used to complete the sorting and optimization of feasible schemes. After scoring, the system selects the result with the highest score from the set of feasible alternatives as the final output.

This generation mechanism organizes path rules, constraint screening and score sorting into unified computing links, so that industrial design innovation can form an interpretable, testable and reusable scheme output structure in the intelligent manufacturing environment. The generated results not only maintain consistency with the high-value path, but also provide a stable foundation for subsequent value enhancement verification and cross-scenario migration.

4 Experimental setup and implementation process

4.1 Intelligent manufacturing product design dataset construction and experimental configuration

This paper focuses on the computational modeling task of product value enhancement driven by industrial design innovation in intelligent manufacturing environment, and constructs a dataset for product design analysis and path identification. The data comes from four product development scenarios of consumer electronics, smart home, light industrial equipment and digital terminals. A total of 1536 product design samples and 18240 industrial design innovation behavior records are collected. Each sample corresponds to a complete design scheme description, structure configuration results, process adaptation information and feedback response records, so as to ensure the unified alignment of design side, manufacturing side and value side data at the sample level.

In the data construction stage, this paper structurally labeled the product appearance form, functional module combination, material and process adaptation relationship, interactive feedback results and market value response. The design attributes include contour level, interface composition, module coupling strength and functional coverage, the manufacturing attributes include machining accuracy, assembly stability, material matching degree and batch process fluctuation, and the feedback attributes include scheme acceptance rate, user interaction retention rate, after-sales consistency and value gain score. After the multi-source feature verification of all samples, they were further matched with the industrial design innovation behavior records one by one to form a standardized data table for path learning.

The experimental platform uses dual-channel Intel Xeon Gold processor, 256GB memory and NVIDIA RTX A6000 graphics card, and the software environment is Python 3.10. The model training and graph calculation processes are deployed in PyTorch 2.1 and Scikit-learn 1.4 environments. In the data preprocessing stage, missing value correction, abnormal record elimination, interval normalization and discrete semantic mapping were completed, and finally the experimental input set that can be used for value label construction, graph association mining and group clustering analysis was generated. In order to ensure the repeatability of subsequent experimental results, the data set is divided into training set, validation set and test set according to the ratio of 7:2:1, and the distribution of product categories and value labels is more consistent. All the records are anonymized, and the samples, actions and labels are organized according to uniform numbering rules, so as to ensure that the subsequent training calls and consistency checks can be completed under the same index system.

4.2 Product value improvement path training and design task execution process

In the stage of model training and task execution, we adopt a unified path learning and scheme generation process to realize the closed-loop calculation from product sample input to value enhancement output. In the training stage, 1536 product design samples and 18240 industrial design innovation behavior records are loaded based on the multi-source feature coding matrix and discrete value labels, and the path construction, rule screening and group mapping are completed in the graph association space. After extracting the high-value paths, the system writes the rule constraints into the scheme generation engine, and performs consistency filtering and sorting output in the candidate space. Table 3 presents the training and execution key configurations.

Table 3: Product value enhancement path training and design task execution configuration

Stage	Input Scale	Core Operation	Parameter Setting
Data Loading	1536 samples	Reading feature encodings and value labels	batch = 128
Graph Association Training	1536 samples	Constructing node relationships and edge-weight matrices	learning rate = 0.001
Path Screening	18,240 records	Extracting high-value paths and pruning	support = 0.08, confidence = 0.67
Cluster Mapping	1536 samples	Generating the sample–rule response matrix	number of clusters = 5
Generation Execution	Dynamic candidate set	Constraint filtering and comprehensive ranking	number of threads = 4

As shown in Table 3, graph association training and path screening determine the constraint space of the generation mechanism, and cluster mapping is used to maintain the structural discrimination of different sample subsets on path responses. The support threshold was set to 0.08, and the confidence threshold was set to 0.67, in order to maintain a balance between path coverage and rule interpretation strength. The number of clusters is set to 5, which is used to correspond to the previous value enhancement pattern. In order to ensure the computational efficiency of candidate schemes in consistency filtering and comprehensive scoring, the generation and execution phase adopts four-thread parallel mode. The whole process completes path learning at the training end and constraint invocation at the execution end, so that the product value improvement path can be transformed into executable design generation logic.

5 Analysis of experimental results and evaluation of product value improvement

5.1 Evaluation indicators of product value improvement path identification

In order to test the discrimination ability of the path identification module in the product design task of intelligent manufacturing, this paper evaluates the path identification accuracy, value response consistency and high-value path retention rate, and compares the method in this paper with the rule-screening method only and the clustering mapping method only. Fig. 3 shows the recognition results of each method under different rule threshold conditions.

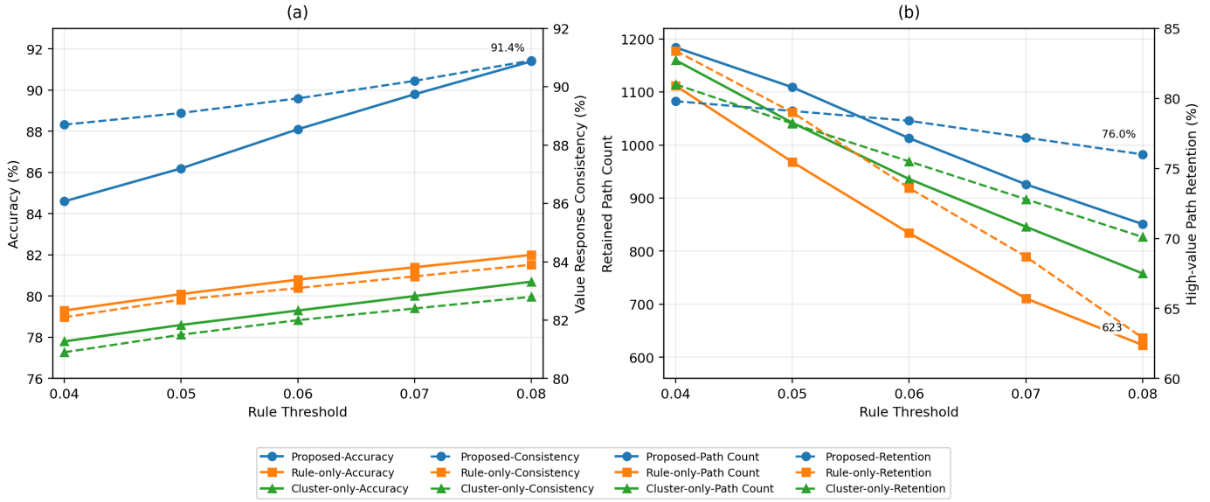


Figure 3: Path identification performance comparison of the methods for different rule thresholds

As shown in Fig. 3, with the rule threshold increased from 0.04 to 0.08, the path identification accuracy of the proposed method increased from 84.6% to 91.4%, the consistency of value response remained above 88.7%, and the retention rate of high-value paths remained stable between 76.0% and 79.8%. This indicates that a stable synergy is formed between graph association modeling, rule learning, and value label supervision. In contrast, the rule-only screening method can retain more candidate paths at a low threshold, but when the threshold continues to increase, the number of paths decreases rapidly, and the average confidence improvement is limited, and only 623 paths are retained in the end. Although the clustring-only mapping method maintains a high coverage in the sample groups, it is insufficient to describe the continuous conduction relationship between design attributes, manufacturing constraints and value results, so the accuracy is always lower than that of the proposed method. The fact that the proposed method stays ahead is related to the simultaneous utilization of design attribute co-occurrence relationships, manufacturing execution constraints, and value label feedback in the path construction phase. After the three types of information enter the same identification process, the screening boundary of the high-value path is clearer, and the low-contribution attribute combination is eliminated in advance, so it can still maintain high accuracy and consistency after the threshold is increased. The set of retained paths has a more stable distribution among different product categories and is also more suitable as an input basis for subsequent group clustering and scheme generation.

5.2 Evaluation of product design innovation group clustering

After extracting the high-value paths, this paper further identifies and analyzes the group structure of the samples in the rule response space. The K-means algorithm is selected in the clustering stage, because the algorithm has a more stable partition result in the high-dimensional sparse rule vector space, and it is easy to maintain the direct mapping relationship between the path rules and the sample population. The number of clusters is searched between 3 and 7, and the average silhouette coefficient and the Davies-Bouldin index are used as the main evaluation indexes. The former is used to describe the consistency within clusters, and the latter is used to measure the separation between clusters. Fig. 4 illustrates the group division results of each method with different number of clusters.

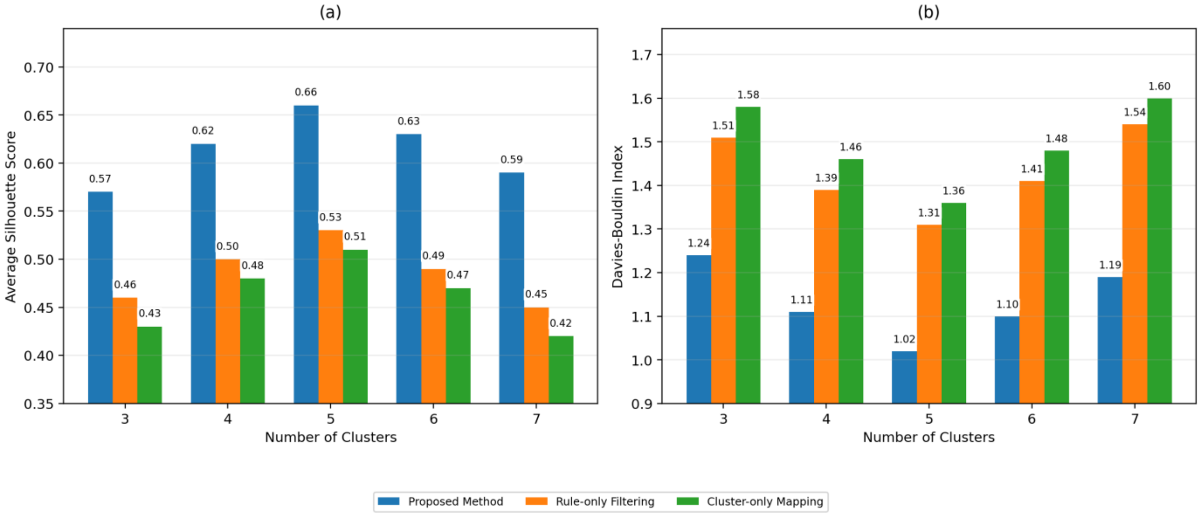


Figure 4: Performance comparison of innovative group structures for product design with different number of clusters

As shown in Fig. 4, when the number of clusters is 5, the average silhouette coefficient of the proposed method reaches 0.66, which is significantly higher than that of the rule-only screening method and cluster-only mapping method, indicating that the rule response matrix constrained by the graph association path and value label has stronger group discrimination ability. Under the same conditions, the Davies-Bouldin index decreases to 1.02, indicating that the boundaries of each group are more compact and the overlap area is smaller. This result is consistent with the setting of five types of product innovation patterns in the previous section, and also shows that the path rules can still maintain a clear semantic structure after entering the clustering space. In addition to the optimal number of clusters, the proposed method always maintains a high silhouette coefficient and a low separation index in the range of 3 to 7, which indicates that the constructed group pattern has good stability. The sample population structure thus formed provides a more reliable input basis for subsequent value enhancement scheme generation and response verification. At the same time, the shift of cluster centers between different product categories is small, indicating that the model has good cross-category adaptability.

5.3 User feedback and value response verification of value enhancement schemes

In order to further verify whether the response difference of value enhancement schemes in different product innovation groups has a stable structure, this paper divides the sample into five categories of product innovation patterns, and constructs two indicators: value response consistency and scheme acceptance rate. The consistency is measured by the average cosine similarity of the score vector within the group, which is used to characterize the convergence degree of the sample response to the generation scheme under the same mode. The acceptance rate is expressed as the proportion of samples whose composite score is above the value threshold and is used to measure the effectiveness of the scheme in the target group. Fig. 5 shows the comparison of the results of different methods in five categories of patterns.

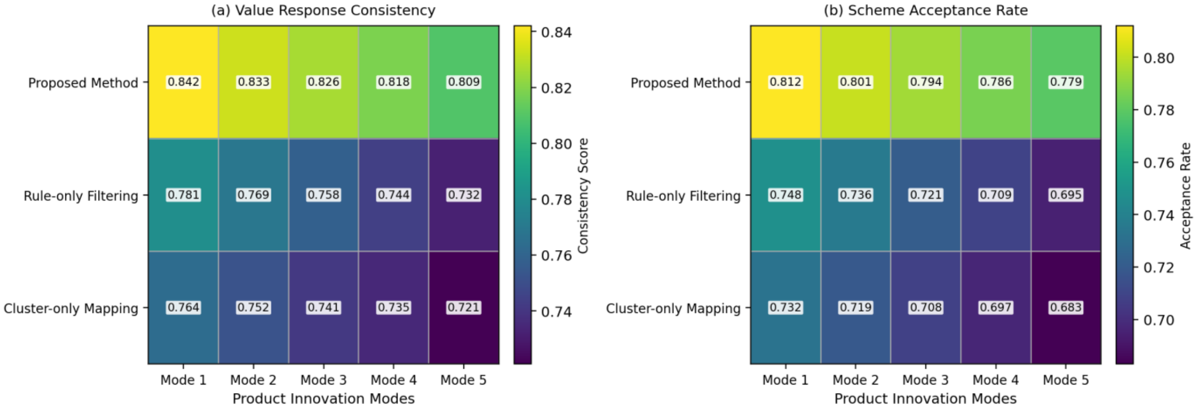


Figure 5: Comparison of value response consistency and scheme acceptance rate of different methods in each product innovation mode

As shown in Fig. 5, the consistency scores of the proposed method in mode 1 and mode 3 reach 0.842 and 0.826 respectively, which are significantly higher than those of the rule-only screening method and the clustering-only mapping method, indicating that the generation scheme constrained by the graph association path and value label is closer to the stable preference structure within the group. In the evaluation of acceptance rate, the proposed method reaches 0.812 in mode 1 and still maintains 0.779 in mode 5, indicating that the proposed method has good adaptation ability in both core value groups and boundary value groups. This result indicates that the collaborative modeling of design attributes, manufacturing constraints and feedback responses enhances the group consistency and value response strength of the scheme output. Combined with the results of path identification and group clustering above, it can be seen that the fluctuation range of the method in the five types of patterns is small, and there is no obvious deviation, indicating that the rule-driven generation mechanism can maintain a relatively stable output boundary under different product categories, and provide a more reliable verification basis for the comparison and analysis of subsequent schemes.

5.4 Comparative analysis of product value feature distribution before and after design innovation

In order to evaluate the influence of design innovation mechanism on the organization mode of product value characteristics, this section compares the functional value contribution distribution and manufacturing adaptation offset, and takes the changes of samples before and after innovation in the five types of product innovation modes as the analysis object. Functional value contribution is used to measure the balance between performance expression, interactive response and market acceptance of different design alternatives, and manufacturing adaptation offset is used to characterize the structural stability of design output during process execution. Furthermore, the value contribution of the pre-innovation part of the sample is mainly concentrated in a single functional module or local interaction improvement, resulting in a weak collaborative relationship between high-value attributes. After innovation, under the constraint of path rules, the linkage of function, process and feedback features is more complete, so the internal distribution boundaries of different modes are clearer, and the overlap area between modes is significantly reduced. This shows that the value expression after innovation no longer depends on the single point of reinforcement, but forms a balanced structural combination.

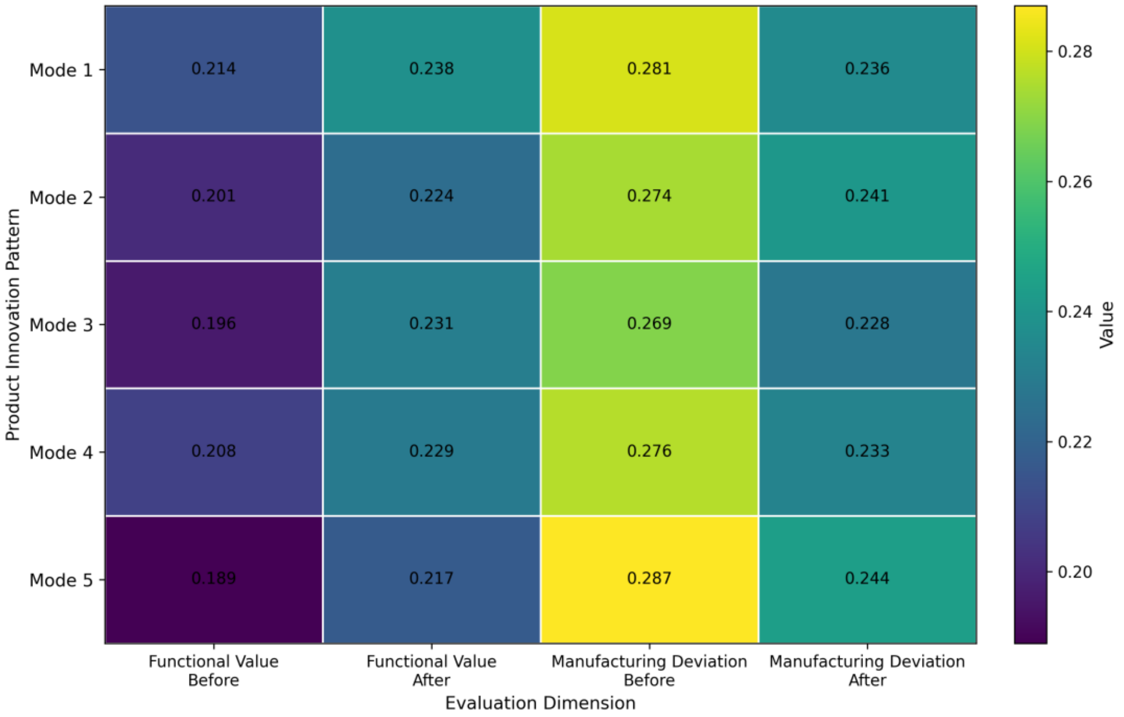


Figure 6: Comparison of product value characteristics distribution before and after design innovation

As shown in Fig. 6, the functional value contribution of each mode increases after innovation, which indicates that path constraint-driven scheme generation can focus design innovation more steadily on high-value attribute combinations. Among them, pattern 3 has the most obvious increase from 0.196 to 0.231, indicating that graph association rules have a stronger guiding effect on functional reorganization and feedback collaboration. At the manufacturing adaptation level, the offset values of the five types of modes dropped below 0.244 after innovation, indicating that the fluctuation range of the generation scheme in the process execution was compressed, and the structural consistency was further enhanced. Compared with the pre-innovation, the feature distribution after innovation is more concentrated, and the cross-mode difference is clearer, indicating that the proposed method not only improves the distribution balance of value features, but also improves the synchronous matching ability of design output on the manufacturing side and the feedback side.

5.5 Testing model stability and generalization across scenarios

Under the cross-scenario design task, in order to verify the stability and generalization adaptability of the proposed method for the product value improvement path, this paper analyzes the stability of rule structure and output consistency. The stability of rule structure is measured by the overlap rate of high-value path set in different tasks, which reflects the ability of the model to retain the core path structure under the condition of task switching. Output consistency is then expressed as the average similarity of schemes obtained by the same value group in different tasks, which is used to measure the continuous maintenance effect of the generation mechanism on value preference. The test tasks cover five types of scenarios, including smart home terminals, wearable devices, desktop interactive products, portable digital devices and light industrial equipment interfaces. Each task contains independent sample sets and independent behavior records to ensure the scene difference and structural diversity. Fig. 7 shows the comparison of the results of each method in five categories of tasks.

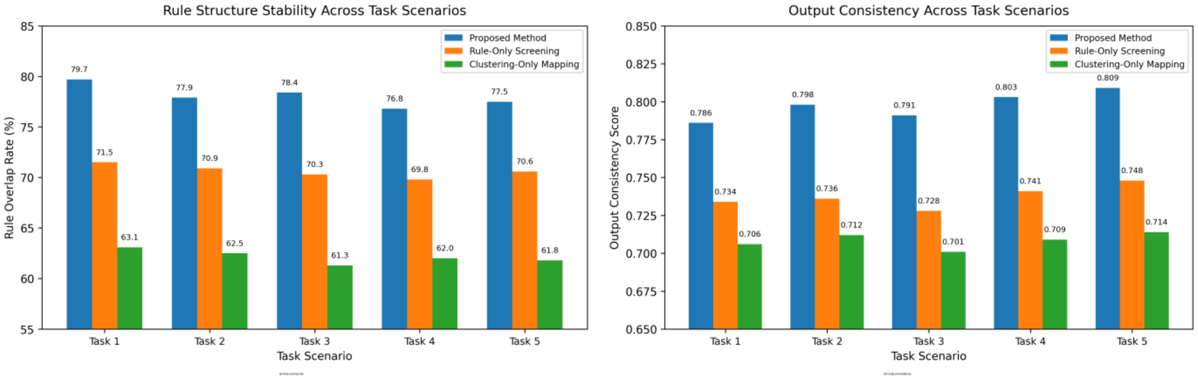


Figure 7: Comparison of model stability and cross-scenario generalization ability under different task scenarios

As shown in Fig. 7, the rule overlap rate of the proposed method in task 1 and task 3 reaches 79.7% and 78.4%, respectively, which is higher than that of the rule-screening method only and the cluster-mapping method only, indicating that the graph association path can still maintain strong structural continuity under the condition of task change. In terms of output consistency, the proposed method achieves 0.798 and 0.809 in task 2 and task 5, respectively, which are higher than those of the comparison methods, indicating that the rule-driven generation mechanism can continuously maintain the value expression boundary in different product scenarios, and maintain good output stability under the condition of task transfer.

6 Discussion

Our method shows comprehensive advantages in multi-dimensional experiments, which do not come from single indicator lifting, but from the synergy of design features, manufacturing constraints, behavioral feedback, and value labels in the same computational framework. The accuracy of path identification reaches 91.4%, and the consistency of value response remains above 88.7%, which indicates that the combination of graph association modeling and rule learning can more stably retain high-value structures. Compared with the methods that only rely on frequency screening or sample adjacent division, the proposed method does not simplify design innovation into local attribute stacking, but incorporates structural relationship, execution state and feedback results into path judgment, so that it can still maintain a clear identification boundary under the condition of threshold change. In the group clustering experiment, the silhouette coefficient of five types of product innovation patterns is 0.66, which indicates that the rule response matrix maintains internal consistency and group separability after entering the clustering space. The resulting pattern structure can not only explain the differences in value formation of different samples, but also provide a stable constraint for subsequent scheme generation. The consistency and acceptance rate of the value enhancement scheme in the five types of patterns maintain a high level, indicating that the generation mechanism realizes the synchronous mapping between path logic, manufacturing adaptation and feedback response. The comparison of value feature distribution before and after design innovation further shows that the combination of high-value attributes presents a more balanced distribution state under the rule constraints, and the manufacturing adaptation offset is also compressed, which means that the scheme output is enhanced at the structure level and the execution level at the same time. In the cross-scenario test, the rule overlap rate and output consistency maintain small fluctuations, indicating that the transfer of the model in different product tasks does not depend on specific category samples, but on a unified coding, path and generation mechanism. These results show that the technology chain constructed in this paper has the characteristics of computational closed-loop. From multi-source feature coding to value label generation, to path mining, pattern recognition and scheme generation, the clear data interface and logical transmission relationship between each stage are maintained, so that the process of industrial design innovation driving product value improvement obtains a more interpretable computational expression.

7 Conclusions

Focusing on the identification and generation of product value improvement paths driven by industrial design innovation in intelligent manufacturing environment, this paper constructs a unified computing framework consisting of multi-source feature coding, behavior label generation, graph association path mining, group pattern recognition and intelligent scheme generation. At the method level, design attributes, functional configurations, process parameters, user interaction records, and market feedback are organized into the same data space. Path rules are no longer dependent on single frequency statistics, but are filtered through graph structure relationships and value label supervision. At the experimental level, based on 1536 product design samples and 18240 industrial design innovation behavior records, the model achieves 91.4% accuracy in path identification task, maintains more than 88.7% consistency in value response verification, and obtains 0.66 silhouette coefficient under five product innovation modes. It indicates that a logical closed loop is formed between path rules, group patterns and generated outputs. The comparison of feature distribution before and after design innovation and cross-scenario tests show that the proposed method can maintain clear value boundaries in different product categories, and support the generation scheme at the level of manufacturing adaptation and feedback response.

It should be pointed out that this paper still has limitations in the modeling scope and experimental coverage. Existing processes are mainly based on structured samples and discrete labels, and complex design semantics, temporal interaction behaviors and dynamic manufacturing disturbances have not been fully incorporated into the same representation framework. Although the rule-driven generation mechanism has strong interpretability, the expression richness in the large-scale candidate space is still constrained. The cross-scenario experiments have covered five types of tasks, but the samples are still focused on typical product categories, and there is still room for expansion of the coverage of highly heterogeneous industrial scenarios. The follow-up research can be promoted from three directions. First, the temporal behavior flow, process sensing sequence and multi-modal semantic information are introduced to enhance the continuity of value path representation. Secondly, the generative model and graph reasoning mechanism are combined to improve the diversity and constraint adaptation ability in the scheme search space. Thirdly, an incremental learning and online update mechanism is constructed to make the product value improvement path maintain stronger adaptive ability in the process of task migration and data iteration.

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