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A Quantitative Model of the Industrial Design Cognitive Process Based on Information Entropy

Jiayi Zhou *

Swinburne College of Shandong University of Science and Technology, Jinan, Shandong, China

***Corresponding author:** Jiayi Zhou. Email: 18514778188@163.com

Abstract

The cognitive process of industrial design is characterized by high complexity and dynamic evolution, and its information change law has long lacked effective mathematical quantitative means. In this study, information entropy theory is introduced into the field of industrial design, and a cognitive process quantification model covering data representation, multi-dimensional entropy calculation, dynamic weight optimization, and time series state prediction is constructed. By integrating the structural information, graphic features, parameter adjustments, and time evolution of the design scheme into the information uncertainty analysis framework, three core indexes of scheme diversity entropy, structural change entropy and parameter adjustment entropy and their dynamic fusion methods are proposed. According to the phase-transition characteristics of the design process, an adaptive entropy weight optimization algorithm driven by feature difference degree is designed, and the Transformer time series prediction model is introduced to realize the automatic identification of the design phase. The experiments are verified based on a process dataset of 80 design cases covering four categories of transportation, smart equipment, home products and industrial equipment. The results show that the stage recognition accuracy of the dynamic information entropy model reaches 93.6%, which is 11.2 percentage points higher than that of the traditional Shannon entropy model, and the mean square error (MSE) and mean absolute error (MAE) are reduced to 0.067 and 0.102 respectively. The ablation experiments further verify that the time evolution module contributes most significantly to the model performance. The research demonstrates that information entropy can effectively quantify the evolution of information from decentralization to centralization in the process of design cognition, and provides a computable analysis framework for the understanding, evaluation and optimization of design process.

Keywords

Industrial design; Quantification of cognitive processes; Information entropy; Dynamic weight optimization; Time series prediction

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1. INTRODUCTION

1.1 Research background and motivation

As a typical knowledge-intensive creative activity, industrial design is far from a non-linear task execution sequence, but a complex cognitive process interwoven with problem reconstruction, scheme generation, judgment screening, and detail polishing. Designers constantly make decisions under condition of limited information [1],[2]. Starting from the fuzzy requirement description, they gradually transform the uncertain design intention into a definite product plan through repeated attempts and revisions [3],[4]. However, for a long time, the evaluation of the design process has mainly relied on the subjective judgment of experts and the quality of the final design results. Each scheme adjustment and each round of iterative optimization in the design process is essentially accompanied by the change of design information distribution, which is the key clue to understanding the cognitive activities of design, but there has been a lack of effective mathematical tools to describe it objectively in the past. In recent years, the popularization of digital design tools has profoundly changed the way design data are generated and recorded. Computer-aided design software, parametric modeling platforms, and collaborative design systems are widely used in the daily work of designers, so that design sketches, 3D models, parameter modification records, and scheme version iteration process data can be systematically retained [5],[6],[7]. These deposited digital traces provide an unprecedented data basis for revealing the internal mechanism of the cognitive process of design. In this context, information entropy, as a classical tool for measuring system uncertainty and information richness in information theory, naturally has the potential to describe the evolution process of information distribution from decentralization to centralization in the design process, which opens up a new mathematical path for the quantitative analysis of industrial design cognitive process. Based on the above understanding, this study attempts to introduce the information entropy theory into the field of industrial design, and build a set of systematic models that can carry out computational expression and intelligent analysis of the design cognitive process, so that the design process can move from the ineffable empirical realm to the measurable and computable research domain.

1.2 Research status at home and abroad

In the field of industrial design process modeling, scholars at home and abroad have carried out a lot of exploratory work. In terms of design process model, the early stage-gate model divides the design process into sequential stages such as requirements analysis, conceptual design, detailed design and production implementation, which provides a basic framework for the structured organization of design activities. The subsequent spiral model and iterative design model further recognize the cyclic feedback characteristics of the design process and emphasize the repetitive nature of scheme evaluation and revision [8],[9]. In terms of design activity analysis methods, methods such as protocol analysis, design log analysis, and design roadmapping are widely used to trace the thinking trajectory and behavior pattern of designers. These methods try to establish the correlation between design behavior and cognitive strategy by encoding key decision points and operation sequences in the design process. Design knowledge representation methods focus on how to transform the empirical rules, morphological grammar and functional structure in design into computer tractable forms, including rule-based knowledge representation, case-based reasoning, and ontology modeling, which lay the foundation for the structured expression of design information [10],[11]. However, most of the above studies focus on the qualitative description of the design process and the classification of behaviors, and the quantitative description of information changes in the design process remains relatively weak.

Information entropy and its applications in the quantification of complex systems provide a direct theoretical tool for this study. As a pioneering contribution of information theory, Shannon information entropy is widely used in communication, statistics, and complex networks by measuring the average information content of a system through probability distribution [12],[13],[14]. On this basis, fuzzy entropy has been extended to deal with the fuzziness and imprecision in systems, and is suitable for dealing with the design concept and semantic information with unclear boundaries. The proposal of multi-scale entropy further addresses the difficulty of describing the multi-level complex characteristics of a system at a single scale, and reveals the hierarchical structure information of the system by calculating the entropy value at different time or space scales. As the core criterion for feature selection and decision tree construction, the information gain method measures the degree of contribution of a certain feature to the reduction of system uncertainty [15],[16]. Although these entropy correlation methods have achieved rich results in the fields of biological signal analysis, mechanical fault diagnosis and financial time series analysis, their application in the field of industrial design is still in its infancy. How to select and adapt the appropriate entropy calculation method according to the specificities of the design process is a key problem to be solved.

The research of intelligent design process computing represents the frontier direction of the intersection of design field and artificial intelligence technology. Data-driven design relies on large-scale design case bases and machine learning algorithms to extract implicit rules from existing design schemes and assist designers in form generation and scheme evaluation. Parametric design analysis enables systematic exploration and optimization of the design space by establishing mathematical relationships between design variables and performance indexes. AI-assisted design methods include generative adversarial networks for generating design images, reinforcement learning for optimizing design strategies, and natural language processing for assisting design requirements analysis [17],[18]. These studies have greatly expanded the possibility boundary of design process automation and intelligence. However, a comprehensive review of the research status of the above three aspects reveals that there are obvious fault lines among the existing work: the design process modeling research lacks quantitative means for the dynamic change of information, the application research of entropy theory has not gone deep into the specific scenario of design cognition, and research on intelligent design computing pays more attention to the quality improvement of design results than to the understanding of the process itself. Specifically, there is a lack of information quantification methods for the dynamic changes of the design process in current research, and the existing information measurement methods are difficult to capture the time-varying characteristics of uncertainty in the design iteration process. The lack of a unified mathematical model to describe the evolutionary complexity of design solutions makes it difficult to compare and integrate different types of design information under the same framework. There is also a lack of design cognitive state computing framework combined with algorithm optimization, which makes the stage identification and state prediction of the design process lack systematic computational support.

1.3 Research content and innovation points

In view of the above lack of research, this paper focuses on the core issue of quantifying the cognitive process of industrial design based on information entropy to carry out systematic research. Firstly, the information entropy quantitative representation model of industrial design process is established. Through the unified coding of multi-dimensional information such as scheme structure, graphic features, parameter changes and time evolution in the design process, a computable data representation framework for the design process is constructed, so that the design cognitive activities can be transformed into quantifiable information features. Secondly, on this basis, a cognitive entropy calculation method of multi-dimensional design information fusion is proposed, which comprehensively considers the information contribution of different levels such as scheme diversity, structural change and parameter adjustment, and forms a quantitative index to comprehensively evaluate the design cognitive state, so as to solve the problem that a single information dimension cannot completely describe the design state. Thirdly, in view of the fact that the industrial design process has obvious stage transformation and dynamic evolution characteristics, a dynamic entropy evolution analysis algorithm is designed. Through the adaptive weight adjustment mechanism and time-series state modeling, the cognitive entropy calculation can be dynamically updated with the design process, so as to accurately reflect the continuous evolution law of the design process from exploration to convergence. Finally, through the construction of experimental data sets containing multiple types of industrial design cases, the proposed quantitative model is systematically verified; the performance of the model in different design stages and its differences from traditional methods are analyzed, and the validity and application boundary of the model are tested.

The innovation of this paper is mainly reflected in the following aspects: first, it constructs a quantitative cognitive-entropy model for the whole process of industrial design, systematically introduces information entropy theory into the field of design cognition research, and provides a new mathematical tool and theoretical perspective for the objective analysis of the design process. Secondly, a multi-dimensional entropy calculation method integrating scheme change information, structural feature information, and design iteration information is proposed, which overcomes the limitation of traditional methods only focusing on design results or single information dimension, and realizes multi-angle comprehensive description of design cognitive state. Thirdly, the dynamic weight optimization algorithm is designed, so that the contribution degree of each information dimension in the model can be automatically adjusted according to the changes of the design stage, breaking through the bottleneck of the fixed-weight mode's inability to adapt to design-stage transitions, and significantly improving the accuracy and adaptability of the cognitive process description. Fourthly, a model verification system based on real design case data sets is established. Through multiple types of design cases, multi-dimensional evaluation indicators and a variety of comparative experiments, the effectiveness, robustness and contribution degree of each module of the model are systematically tested, which provides a reliable experimental basis for the engineering application of the model.

2. QUANTITATIVE MODEL OF THE INDUSTRIAL DESIGN COGNITIVE PROCESS BASED ON INFORMATION ENTROPY

2.1 Industrial design process data representation model

The process of industrial design is essentially a dynamic evolution process formed by information input, scheme generation, scheme adjustment and result optimization. Traditional industrial design evaluation usually focuses on the final design results, but ignores the process characteristics such as scheme change, structural adjustment and design information accumulation in the design process, which makes it difficult to achieve quantitative description of design cognitive activities. In order to realize the digital expression of industrial design cognitive process, this paper abstracts the design process into multidimensional data space, and establishes a design process data representation model oriented to information entropy calculation through unified coding of design objects, design behaviors and design evolution process.

In the process of model building, the industrial design process data are divided into four types: scheme structure information, graphic feature information, parameter change information and time evolution information. Among them, the scheme structure information is used to describe the organizational relationship of product form, the division of functional modules and the spatial correlation between design elements. Graphic feature information is used to express the outline, curve, layout and visual feature changes in the design scheme [19]. Parameter change information is used to record the adjustment process of size, proportion, material property and performance index during the design process; The time evolution information is used to describe the continuous change of the scheme state in different design stages. Therefore, the design process data structure is expressed as:

$$D = \{D_s, D_g, D_p, D_t\} \tag{1}$$

Where D represents the complete design process data set; D_s represents the scheme structure information data; D_g represents graph feature information data; D_p represents parameter change information data; D_t represents time evolution information data.

In order to eliminate the dimensional and scale differences between different types of design data, the original design data are normalized, so that the data of different dimensions can participate in the subsequent information entropy calculation. The normalization process is expressed as:

$$X_i' = \frac{X_i - X_{min}}{X_{max} - X_{min}} \tag{2}$$

Where X_i' represents the normalized design eigenvalue; X_i represents the original design data; X_{max} and X_{min} denote the maximum and minimum values in this feature dimension, respectively.

2.2 Design information entropy calculation model

The industrial design process is characterized by obvious information uncertainty. In the early stage of design, designers usually need to explore a large number of possible solutions, and the design information is scattered. As the design process advances, the scheme is gradually screened and optimized, and the information is gradually concentrated. Therefore, information entropy can be used to describe the degree of information complexity, and the state of scheme change in the design process.

This paper establishes a design complexity evaluation model based on Shannon information entropy theory. When the design scheme changes greatly and there are many possible states, the information distribution becomes more dispersed and the entropy value increases. When the design scheme becomes gradually stable and the information is concentrated in a few optimization directions, the entropy decreases. Therefore, information entropy can effectively reflect the degree of exploration and convergence trend in the design process.

According to the characteristics of industrial design cognitive process, this paper further constructs three types of core entropy indexes, including scheme diversity entropy, structural change entropy, and parameter adjustment entropy.

Scheme diversity entropy is used to measure the degree of information dispersion between different scheme states in the design process:

$$H_s = -\sum_{i=1}^{m} p_i^s \ln p_i^s \tag{3}$$

Where, H_s represents the scheme diversity entropy; p_i^s represents the occurrence probability of the i-th design scheme; m denotes the number of schemes.

Structural change entropy is used to describe the degree of change in the internal organizational relationship of a design object:

$$H_g = -\sum_{j=1}^{k} p_j^g \ln p_j^g \tag{4}$$

Where H_g represents the entropy of structural change; p_j^g represents the characteristic probability of the j-th type of structural change; k represents the number of structural change types.

Parameter adjustment entropy is used to evaluate the uncertainty of parameter adjustment in the design optimization process:

$$H_p = -\sum_{r=1}^{q} p_r^p \ln p_r^p \tag{5}$$

Where H_p represents parameter adjustment entropy; p_r^p represents the change probability of the r-th parameter; q denotes the number of parameter adjustment categories.

Based on the above three dimensions, the quantitative index of industrial design cognitive process is constructed:

$$H_c = \alpha H_s + \beta H_g + \gamma H_p \tag{6}$$

Where H_c represents the cognitive entropy of comprehensive design; α, β and γ represent the weight coefficients of the three factors of scheme diversity, structural change and parameter adjustment respectively, and satisfy the following requirements:

$$\alpha + \beta + \gamma = 1 \tag{7}$$

By integrating the cognitive entropy index, the implicit cognitive changes in the design process can be transformed into computable data features, and the quantitative description of the design exploration, adjustment and optimization process can be achieved.

2.3 Multi-source design information fusion model

Because the cognitive process of industrial design is affected by many factors, it is difficult for a single information entropy index to completely describe the design state. Therefore, this paper establishes a multi-source design information fusion model, transforms the design data from different sources into a unified information entropy feature, and realizes the comprehensive evaluation through the weight optimization method.

The overall process of the model includes five stages: design data input, feature extraction, entropy feature calculation, information fusion and comprehensive cognitive entropy output.

Based on the data representation model in Section 2.1, feature extraction is carried out on the input design process data to form a design feature set:

$$F = \{f_1, f_2, \dots, f_n\} \tag{8}$$

Where, F represents the set of design features; f_i represents the i-th design feature variable; n is the number of features.

Then the entropy weight method is used to determine the importance of different features:

$$w_i = \frac{1 - H_i}{\sum_{i=1}^{n}(1 - H_i)} \tag{9}$$

Where w_i represents the weight of the i-th design feature; H_i represents the information entropy of the i-th feature.

On this basis, feature correlation analysis is introduced to modify the correlation degree between different features:

$$w_i' = w_i(1 + r_i) \tag{10}$$

Where w_i' represents the optimized feature weight; r_i represents the correlation coefficient between the i-th feature and the design evaluation objective.

Finally, the integrated cognitive entropy is obtained:

$$H_{total} = \sum_{i=1}^{n} w_i' H_i \tag{11}$$

Where, H_{total} represents the output result of comprehensive cognitive entropy.

2.4 Dynamic entropy evolution model of design process

The cognitive process of industrial design is not a static state, but constantly changing in the time dimension. Therefore, the design process cannot be accurately described only through the information entropy of a single time node, and a dynamic entropy evolution model needs to be established to continuously analyze the transformation of design stages.

In order to describe the state change of adjacent stages in the design process, entropy change rate is introduced:

$$\Delta H_t = H_t - H_{t-1} \tag{12}$$

Where, ΔH_t represents the change of information entropy in stage t relative to the previous stage; H_t represents the cognitive entropy value of the current time node; H_{t-1} represents the cognitive entropy value of the previous time node.

The dynamic evolution index is further defined to comprehensively represent the current entropy level and its changing trend:

$$E_t = \lambda H_t + (1 - \lambda)\Delta H_t \tag{13}$$

Where E_t represents the dynamic state index of the design process; λ represents the adjustment parameter between static entropy and change entropy, which is used to balance the influence weight of current state and change trend on the judgment of design stage.

3. INFORMATION ENTROPY COGNITIVE CALCULATION METHOD BASED ON IMPROVED ALGORITHM

3.1 Adaptive entropy weight optimization algorithm

Aiming at the problem that the fixed weight of the traditional entropy model cannot adapt to the change of the design process, this paper proposes a data-driven dynamic entropy weight adjustment method. Instead of presetting fixed weights, this method automatically updates weights according to the information contribution degree of various information features in different design stages.

Firstly, the algorithm extracts feature from the design process data, and transforms the scheme structure, graphic features, parameter changes and time evolution information into a unified feature space:

$$F = \{f_1, f_2, \dots, f_m\} \tag{14}$$

Where, F represents the feature set of the design process; f_i represents the i-th design feature; m represents the number of design features.

In order to measure the ability of different design features to distinguish between stages, this paper introduces the feature difference index. For the j-th feature, its difference degree in different design states is measured by variance:

$$V_j = \frac{1}{n}\sum_{i=1}^{n}(f_{ij} - \bar{f}_j)^2 \tag{15}$$

Where V_j represents the difference degree of the j-th feature; f_{ij} represents the value of the j-th feature in the i-th design state; $\bar{f}_j$ represents the mean value of this feature in all states; n denotes the number of design states.

The higher the feature difference is, the more significant the change of the feature between different design stages is, and the more discriminative information it contains. Therefore, the feature contribution degree is calculated according to the difference degree:

$$C_j = \frac{V_j}{\sum_{j=1}^{m} V_j} \tag{16}$$

Where C_j represents the information contribution rate of the j-th feature; m represents the total number of features.

On this basis, a time-driven mechanism is introduced to enable the model to adjust the feature weights according to the changes in the design stage:

$$W_j(t) = \mu C_j(t) + (1 - \mu)W_j(t - 1) \tag{17}$$

Where $W_j(t)$ represents the dynamic weight of the j-th feature in the t-th stage; $C_j(t)$ represents the feature contribution rate of the current stage; $W_j(t-1)$ represents the weight of the previous stage; μ denotes the weight update parameter.

After dynamic weight adjustment, the optimized cognitive entropy calculation model is formed:

$$H_c(t) = \sum_{j=1}^{m} W_j(t)H_j(t) \tag{18}$$

Where $H_c(t)$ represents the comprehensive cognitive entropy after optimization at stage t; $H_j(t)$ represents the information entropy of the j-th design feature in the current stage.

Through the process of feature extraction, difference calculation, weight update and cognitive entropy output, the algorithm realizes the transformation of design information weight from static allocation to dynamic adjustment.

Table 1 shows the main computational modules of the adaptive entropy weight optimization algorithm.

Table 1. Process structure of adaptive entropy weight optimization algorithm

Phase of computation	Enter the information	Core computing method	The output result
Feature extraction stage	Design process data	Multidimensional feature coding	Design feature set
Difference calculation stage	Characteristic data	Analysis of variance	Characteristic contribution degree
Weight update stage	Degree of contribution sequence	Dynamic weight adjustment	Time weight parameter
Entropy calculation stage	Optimizing the weight	Weighted fusion computation	Dynamic cognitive entropy

Table 1 shows that the algorithm enables different design information to participate in cognitive calculation according to the importance of the current stage by introducing a dynamic weight update mechanism. Among them, the feature difference calculation is responsible for identifying the key design information, and the weight update mechanism is responsible for adapting to the changes of the design process, and finally the information entropy evaluation model with dynamic adaptability is formed.

3.2 Cognitive state prediction algorithm based on time series model

The industrial design process has obvious time continuity, and there is a state inheritance relationship between different design stages. Therefore, only the cognitive entropy value of the current time node cannot fully describe the changing trend of the design process. Therefore, this paper establishes a cognitive state prediction algorithm based on time series model, takes continuous cognitive entropy sequence as input, and realizes state recognition in the design stage through deep time series model.

Firstly, the comprehensive cognitive entropy of each time node in the design process is arranged in time order to form the cognitive entropy time series:

$$H = [H_1, H_2, \dots, H_T] \tag{19}$$

Where, H represents the complete cognitive entropy time series; H_t represents the comprehensive cognitive entropy value at the t-th time node; T denotes the time series length.

In order to enhance the ability of the model to utilize historical information, the sliding time window is used to construct the input sequence:

$$X_t = [H_{t-k}, H_{t-k+1}, \dots, H_t] \tag{20}$$

Where, X_t represents the input sequence of the t-th time node; k represents the time window length. Transformer Encoder is used as the temporal feature extraction module to establish the association between different time nodes through attention mechanism [20],[21]. The attention calculation process is expressed as:

$$\text{Attention}(Q, K, V) = \text{Softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{21}$$

Where Q represents the query matrix; K represents the key matrix; V represents the value matrix; d_k represents the feature dimension.

Through the attention mechanism, the model can automatically learn the importance of cognitive entropy changes in different time stages. At the same time, in order to further strengthen the expression of Temporal information, the Temporal Attention mechanism is introduced [22]:

$$a_t = \frac{e^{s_t}}{\sum_{i=1}^{T} e^{s_i}} \tag{22}$$

Where a_t represents the attention weight of the t-th time node; s_t represents the time node importance score.

After time sequence coding, the model outputs the design state representation:

$$Y = f(X; \theta) \tag{23}$$

Where, Y represents the design cognition state; X represents the input entropy sequence; Let θ denote the model parameters.

According to the model output, the automatic identification of different stages of the industrial design process can be realized, including the scheme exploration stage, scheme expansion stage, scheme convergence stage and optimization stage. Table 2 describes the structure of cognitive state prediction based on the time series model.

Table 2. Composition of temporal cognitive state prediction models

Modules	Function	Input in	Output of goods
Input coding module	Construct the design entropy sequence	Cognitive entropy data	Time series characteristics
Transformer encoder	Extract the long-run dependencies	Characteristics of sequence	Hidden state representation
Temporal attention	Calculating time importance	The hidden state	Weighted time characteristic
State mapping module	Generate status categories	Feature of fusion	Design phase status

As can be seen from Table 2, the model solves the problem that the traditional model is difficult to describe the long-term evolution relationship through Transformer Encoder, and strengthens the information expression of key time nodes through Temporal Attention, so that the design process can change from static evaluation to continuous state analysis.

3.3 Overall architecture design of the model

Based on the aforementioned information entropy calculation method, adaptive entropy weight optimization algorithm and time series state prediction algorithm, this paper constructs the cognitive quantitative computing framework of industrial design to realize the complete calculation process from design data input to cognitive state evaluation.

The overall model includes five parts: data layer, feature layer, entropy calculation layer, algorithm layer and output layer. The data layer is mainly responsible for the management of design case data, and uniformly stores the design scheme, structural information, graphic information, parameter information and time records to provide data basis for subsequent calculation. The feature layer is responsible for transforming the original design data into computable features, including structural features, graphical features, parametric features, and time series features. The entropy calculation layer is based on the information entropy theory to calculate the complexity of different design features and form a multi-dimensional cognitive entropy expression. The algorithm layer includes dynamic entropy weight optimization module and time series prediction module, and realizes dynamic analysis of design process through adaptive weight adjustment and time series modeling. The output layer generates the description of the design process state according to the calculation results of the model, including the change trend of cognitive entropy, the state of the design stage and the direction of scheme evolution. The overall model is expressed as:

$$M = \{D, F, H, W, Y\} \tag{24}$$

Where M represents the cognitive quantitative model of industrial design; D represents the design data; F represents the feature set; H represents information entropy feature; W represents dynamic weight; Y represents the design state output. Table 3 presents the overall model architecture composition.

Table 3. Framework structure of industrial design cognitive quantitative calculation

Level of hierarchy	Main functions	The key approach	Corresponding output
The data layer	Design data organization	Case database construction	Original design data
Layer of features	Design information representation	Feature extraction and coding	Multidimensional eigenvectors
Entropy calculation layer	Information complexity calculation	Information entropy model	Cognitive entropy feature
Algorithm layer	Analysis of dynamics	Entropy weight optimization and time series model	State analysis model
The output layer	Expression of results	State mapping	Design process evaluation

It can be seen from Table 3 that the proposed model forms a complete calculation process from data acquisition, feature expression, entropy calculation, dynamic optimization to state prediction. Compared with the traditional information entropy model, this framework not only focuses on the quantification of design information, but also further considers the dynamic change law in the design process, providing a unified method basis for subsequent experimental verification and model performance evaluation.

4. EXPERIMENTAL VERIFICATION AND PERFORMANCE ANALYSIS

4.1 Construction of experimental data set

In order to verify the effectiveness of the quantitative model of industrial design cognitive process based on information entropy in the actual design process analysis, this paper constructs the industrial design process data set, and conducts process analysis on different types of product design cases. Since the research focus of this paper is on the evolution law of design process information rather than the evaluation of design results, the experimental data mainly focus on the change characteristics of design schemes in different stages, including scheme structure adjustment, pattern change, parameter modification process and version iteration information.

The experimental data mainly comes from the public industrial design case database, product design database, CAD design process files, and historical design scheme iteration records [23]. Among them, open-source industrial design cases are mainly used to obtain complete design process information; The product design database is used to supplement the structural and morphological data of different types of products; CAD design files are used to extract parameter changes and model evolution information. Historical design scheme version data are used to describe phase transition characteristics during the design process.

In order to ensure that the experimental data can cover different levels of design complexity, this paper selects representative industrial product design cases, including transportation vehicles, intelligent equipment, household products and industrial equipment. Each case contains multiple design versions, and the change degree of design information is calculated by the difference between versions. Using feature difference calculation method for the degree of change between different design versions:

$$\Delta X_t = X_t - X_{t-1} \tag{25}$$

Where, ΔX_t represents the design change of the t-th version compared with the previous version; X_t represents the design characteristics of the current version; X_{t-1} represents the design features of the previous version.

The experimental data set finally contains information such as design cases, the number of versions, feature dimensions and labels in the design stage, and the specific composition is shown in Table 4.

Table 4. Composition of experimental data set of industrial design process

Category of data	Number of cases	Average number of versions	Dimension of feature
Design of vehicle	18	8.6	42
Intelligent product design	25	6.9	38
Home product design	22	7.4	35
Industrial equipment design	15	9.2	46

It can be seen from Table 4 that the experimental data covers different types of industrial design objects, and the average number of versions is more than 6, which can meet the requirements of dynamic analysis of the design process. Among them, the number of industrial equipment design versions is the highest, reaching 9.2, mainly because complex product design usually needs to go through more structural optimization processes. Different types of cases maintain certain differences in feature dimensions, which enables the model to verify the information entropy expression ability under different design complexity levels.

In order to further analyze the data scale and the distribution of design stages, Figure 1 shows the data distribution of different design stages in the experimental data set.

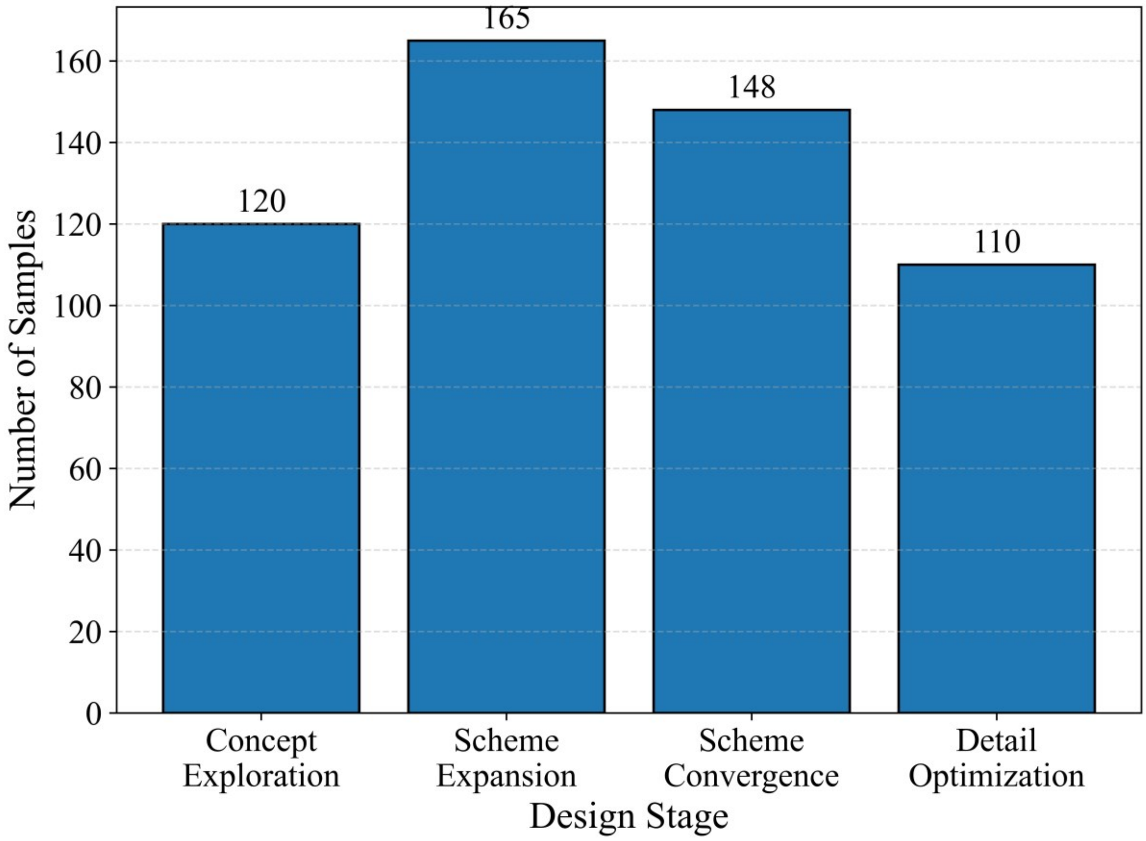

Figure 1. Phase distribution of industrial design experiment data

Figure 1 shows that the experimental data cover the complete design process, and there are a large number of samples in the scheme expansion stage and scheme convergence stage, which can better reflect the rapid information change and scheme screening process in the design process and provide effective data basis for subsequent cognitive state identification.

4.2 Validity verification of information entropy model

In order to verify whether the information entropy model can effectively describe the rules of information change in the process of industrial design, this paper calculates the cognitive entropy values of different design stages, including the initial scheme stage, the scheme evolution stage and the final optimization stage. The experimental results are shown in Table 5.

Table 5. Results of cognitive entropy changes in different design stages

Type of Case	Initial scheme entropy	Scheme evolution entropy	Final optimization entropy	Entropy change trend
Design of vehicle	0.84	0.63	0.36	Continue to decline
Intelligent device design	0.79	0.58	0.32	Continue to decline
Home product design	0.76	0.55	0.35	Gradually stabilize
Industrial equipment design	0.88	0.67	0.41	Clear convergence

It can be seen from Table 5 that different types of design cases all show a trend of gradual decline in cognitive entropy. In the initial design stage, the entropy value is high due to the large scope of scheme exploration and the scattered distribution of design information. With the continuous screening and optimization of the scheme, the design information is gradually concentrated, and the entropy value is significantly reduced in the final optimization stage. Among them, the initial entropy of industrial equipment design is the highest, reaching 0.88, indicating that complex product design has higher information uncertainty.

In order to further observe the dynamic change rule in the design process, the change curve of cognitive entropy of typical cases is drawn, as shown in Figure 2.

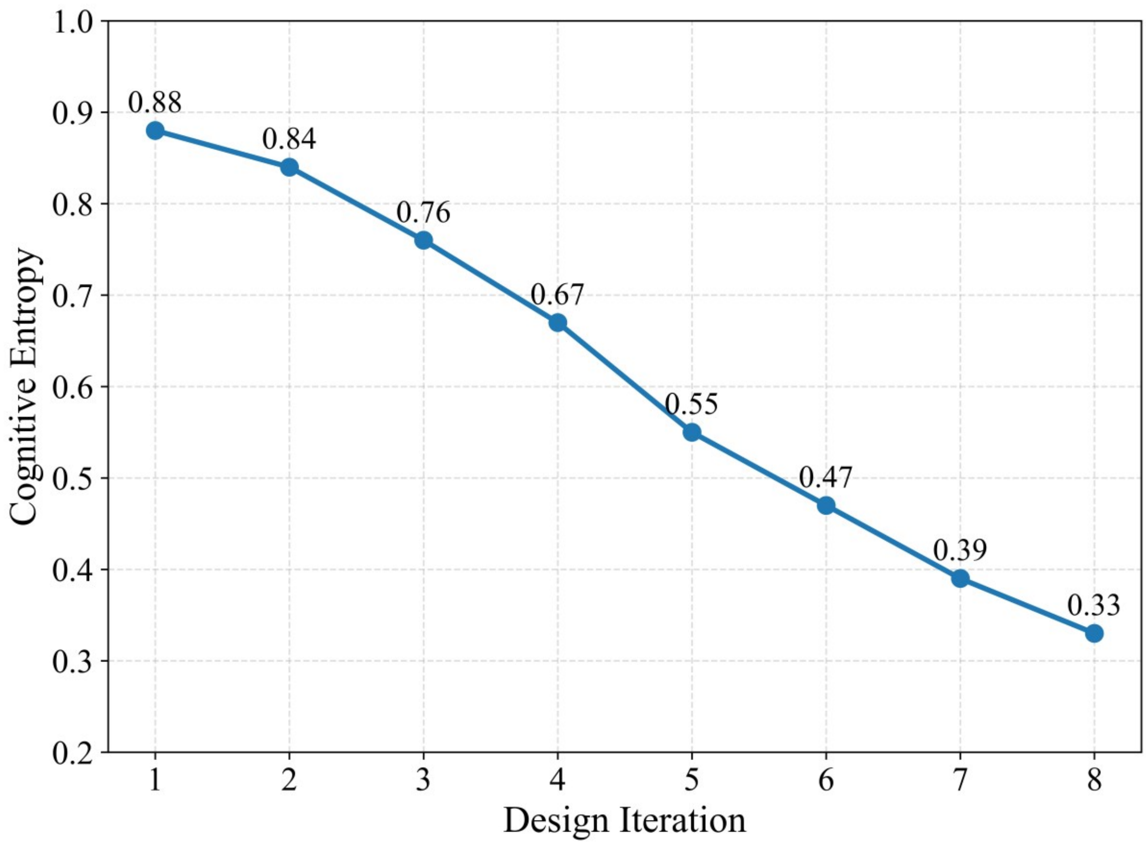

Figure 2. Cognitive entropy evolution curves of typical industrial design cases

It can be observed from Figure 2 that the cognitive entropy in the early design stage is at a high level and gradually decreases with the increase of the number of design iterations. In the scheme exploration stage, the entropy value changes greatly, indicating that there is high uncertainty in the design direction. After entering the scheme optimization stage, the entropy change tends to be smooth, indicating that the design state is gradually stable. This change rule is consistent with the development process of industrial design from divergence exploration to convergence optimization, which proves that the information entropy model can effectively express the complexity change of design process.

4.3 Algorithm comparison experiment

In order to verify the effectiveness of the dynamic information entropy model proposed in this paper compared with the traditional methods, the traditional Shannon entropy model, entropy weight evaluation model, fuzzy entropy model and the dynamic information entropy model of this paper are selected for comparative experiments.

The main differences between different models lie in the adjustment mode of information weight, the ability to express information uncertainty and the ability to model dynamic processes.

The evaluation indexes include classification accuracy, mean square error (MSE), mean absolute error (MAE) and model stability index.

The classification accuracy is calculated as follows:

$$Accuracy = \frac{N_c}{N} \tag{26}$$

Where N_c represents the number of correctly identified samples; N denotes the total number of samples.

The mean square error is calculated as follows [24],[25],[26]:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \tag{27}$$

Where y_i represents the real design state; $\hat{y}_i$ represents the predicted state of the model; N is the number of samples.

The meaning absolute error is calculated as follows [27],[28],[29]:

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}_i| \tag{28}$$

Where, MAE represents the average level of forecast error. The performance pairs of different algorithms are shown in Table 6.

Table 6. Performance comparison of different information entropy models

The Method	MSE	MAE	Index of stability
Shannon entropy model	0.146	0.213	0.76
Entropy weight evaluation model	0.118	0.176	0.81
Fuzzy entropy model	0.104	0.159	0.84
Dynamic information entropy model	0.067	0.102	0.91

Table 6 shows that different models can achieve a certain degree of design state identification, but the dynamic information entropy model shows better comprehensive performance. Both MSE and MAE are significantly reduced, indicating that dynamic weight adjustment and time series information fusion can effectively reduce model prediction errors.

The performance of different models in the identification process of the design phase is further analyzed, as shown in Figure 3.

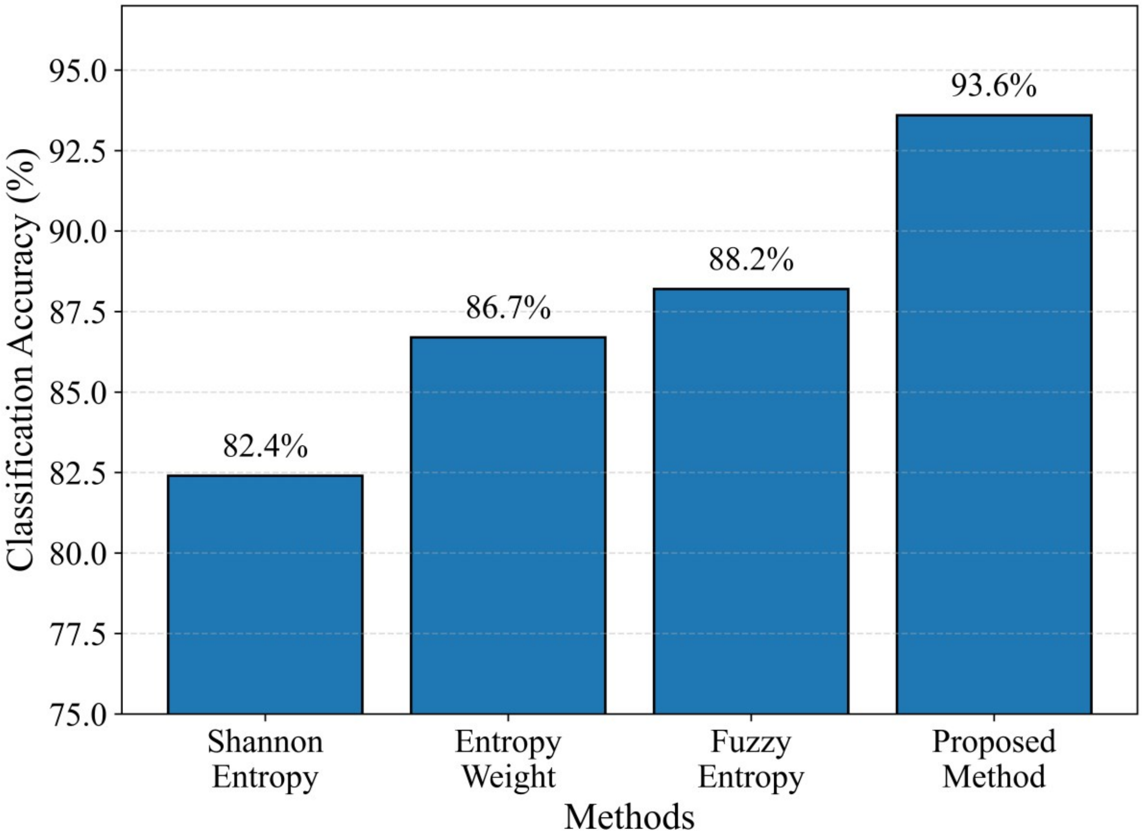

Figure 3. Comparison of design state recognition ability of different algorithms

Figure 3 shows that the identification ability of the traditional model is relatively weak in the scheme exploration stage, mainly because the design information changes are complex in this stage, and the fixed weight method is difficult to accurately describe the information contribution. The dynamic information entropy model improves the ability of information expression in the complex design stage by adjusting the weight in real time and combining the characteristics of time series.

4.4 Ablation Experiments

In order to further analyze the influence of each component module of the model on the overall performance, this paper designs an ablation experiment to remove the dynamic weight module, multi-source information fusion module and time evolution analysis module respectively, and compares the differences between the complete model and different simplified models.

The experimental setup is as follows:

(1) The dynamic weight module is removed and only the traditional fixed weight calculation is retained;

(2) Remove the multi-source information fusion module and use only a single design information for calculation;

(3) The time evolution analysis module is removed, and only static entropy evaluation is carried out.

The different model structures are shown in Table 7 below.

Table 7. Ablation experimental model Settings

Model of experiment	Dynamic weight module	Multi-source fusion module	Time evolution module
The complete model	√	√	√
Model A	×	√	√
Model B	√	×	√
Model C	√	√	×

Through the above experiments, it is possible to analyze the importance of different algorithm modules for the quantification of design cognitive processes. The results of ablation experiments are shown in Table 8.

Table 8. Experimental results of model module ablation

The model	Classification accuracy /%	MSE	MAE
The complete model	93.6	0.067	0.102
Model A	87.9	0.113	0.168
Model B	89.4	0.097	0.145
Model C	86.8	0.121	0.179

Table 8 shows that the model performance decreases after removing any module. Among them, the performance decreases most obviously after removing the time evolution module, which indicates that the design process has obvious time dependence. The accuracy decreases significantly after removing the dynamic weight module, indicating that there are changes in the information contribution at different design stages, which requires adaptive adjustment. Although the influence of multi-source information fusion module is relatively small, it can still improve the expression ability of the model to complex design information.

5. CONCLUSIONS AND PROSPECTS

5.1 Research Conclusions

Focusing on the core problem that the cognitive process of industrial design is difficult to quantify objectively, this study introduces the theory of information entropy into the field of design process analysis, and constructs a complete quantitative model from data representation, entropy calculation to dynamic evolution. Through the unified modeling and fusion calculation of the scheme structure information, graphic feature information, parameter change information and time evolution information in the design process, the research realizes the transformation of the design cognition state from qualitative description to quantitative representation. The experimental results show that the proposed comprehensive cognitive entropy index can effectively reflect the internal law of the transformation from divergent exploration to convergent optimization in the design process. Different types of design cases show a consistent trend of continuous decline in cognitive entropy in the initial scheme stage, scheme evolution stage and final optimization stage, which is highly consistent with the cognitive behavior characteristics in industrial design practice. In terms of model performance verification, the dynamic information entropy model is superior to the traditional Shannon entropy model, entropy weight evaluation model and fuzzy entropy model in terms of classification accuracy, mean square error and mean absolute error, which verifies the effectiveness of the dynamic weight adjustment mechanism and time series modeling strategy in improving the accuracy of design state recognition. Ablation experiments further show that the time evolution analysis module makes the most significant contribution to the overall model performance, followed by the dynamic weight module, and the multi-source information fusion module is also indispensable. The three together constitute the core support for the performance improvement of the complete model. In general, this study verifies the theoretical feasibility and practical effectiveness of information entropy as a quantitative tool for the cognitive process of industrial design, and provides a new analytical perspective and calculation path for the understanding, evaluation and optimization of the design process.

5.2 Research Contribution

The core contributions of this study are at three levels: theoretical, methodological and engineering. At the theoretical level, this study breaks the paradigm limitation of traditional industrial design evaluation that mainly relies on design results and subjective experience of experts, and systematically introduces information entropy, a mathematical tool from the field of communication, into the study of design cognitive process, which establishes a new theoretical basis for quantitative analysis of design activities. By integrating the process of design scheme change, structural organization adjustment and parameter optimization into the information uncertainty analysis framework, this study reveals the evolutionary nature of information distribution in the process of design cognition from decentralization to centralization and from disorder to order, which enriches and expands the methodology system of design science. At the method level, this study proposes a cognitive entropy calculation method for multi-dimensional design information fusion, which effectively solves the problem that different types of information are difficult to quantify uniformly in the design process. At the same time, the adaptive entropy weight optimization algorithm is innovatively designed, so that the model can dynamically adjust the contribution weight of each information dimension according to the change of design stage, which overcomes the limitation that the traditional fixed weight method cannot adapt to the transformation of design stage. In addition, the cognitive state prediction algorithm based on time series model elevates the static entropy evaluation to the continuous evolution process analysis, which makes automatic identification possible in the design stage. At the engineering level, the cognitive quantitative computing framework constructed by the research provides a practical algorithm basis for the development of intelligent design analysis system, and relevant methods can be integrated into digital design tools to realize real-time monitoring and stage judgment of the design process, and provide data support for design management decision-making and design quality assessment, which has certain application and promotion value.

5.3 Future Work

Although this study has achieved some results in theoretical modeling and experimental verification, there are still several directions worthy of further exploration. In terms of design knowledge representation, the current model mainly relies on quantifiable information such as scheme structure, graphic features and parameter changes for entropy calculation, while the unstructured information such as designers' tacit knowledge, empirical intuition and user demand semantics in the design process has not been fully incorporated into the quantitative framework. In the future, we can explore the deep integration of knowledge representation methods such as semantic analysis of design sketches, design intention recognition and user preference modeling with information entropy model, so as to improve the model's ability to express the overall picture of design cognition. In terms of data basis, the experimental data set constructed in this study covers transportation vehicles, intelligent equipment, home products, industrial equipment and other categories, but the sample size and data dimension are still limited. In the future, large-scale, multi-type and standardized industrial design process database needs to be further established to provide more sufficient data support for the deep training and generalization ability verification of the model. In terms of technology integration, the current model focuses on quantitative evaluation and stage identification of design cognitive state, which has not yet formed a closed loop with design content generation. In the future, cognitive entropy index can be explored as the feedback signal of generative artificial intelligence design system to guide the generative model to maintain sufficient diversity in the scheme exploration stage and focus on high-value design direction in the convergence stage. Realize the co-optimization of design process evaluation and design content generation. In terms of engineering application, automated design process evaluation tools can be developed based on the quantitative framework proposed in this study in the future to realize real-time identification of design stage, automatic evaluation of design efficiency, and intelligent recommendation of design scheme evolution path, and promote the further development of industrial design process analysis from manual experience judgment to data-driven and intelligently assisted direction.

Abbreviations

MSE, Mean Square Error;

MAE, Mean Absolute Error;

CAD, Computer-Aided Design.

Supplementary Material

Not applicable.

Appendix

Not applicable.

Ethics approval and consent to participate.

This study did not involve human participants, animal subjects, or any data requiring ethical approval. Therefore, ethics approval and consent to participate are not applicable.

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Competing interests

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Author contributions

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Data availability

The data that support the findings of this study are available upon request from the corresponding authors, **J.Z.**

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Declaration of AI and AI-assisted Technologies in the Writing Process

During the writing of this article, the author used DeepSeek for spelling and grammar checking. After using this tool, the author reviewed and edited the content as needed and assumes full responsibility for the final published content.

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