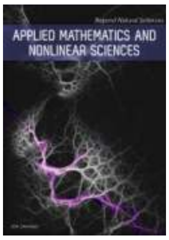
Applied Mathematics and Nonlinear Sciences, 9(1) (2024) 1-21



Applied Mathematics and Nonlinear Sciences

https://www.sciendo.com

Research on the construction of industrial product design and service platform based on KANO-AHP model

Ying Dai[1], Shusen Zhang[1,†]

1. Lishui University, Lishui, Zhejiang, 323000, China.

Submission Info

Communicated by Z. Sabir
Received January 30, 2023
Accepted June 28, 2023
Available online December 18, 2023

Abstract

This paper utilizes the KANO model to establish the nonlinear relationship between the degree of availability of requirements and user satisfaction and determines the importance of customer requirements through AHP analysis. An industrial product design and service platform based on the KANO-AHP model is then constructed, and the key factors for the success of industrial product design are derived by unifying and categorizing the quality characteristics of the products or services, and the management strategies for the key factors are explored. To verify the effectiveness of the constructed platform, user requirements and performance are tested and analyzed. The results show that in the simulation of the number of users is less than 8000, the average time for the server side to respond to requests is basically unchanged, maintained at 10ms, all requests can be processed in time, and the modular task reorganization and allocation method used by the platform convergence of the number of iterations fluctuates less, with the amplitude of the interval in [4.06, 25.09]. The industrial product design and service platform based on this research is capable of meeting the customer's demands for product services.

Keywords: KANO model; AHP analysis; Demand importance; Service platform; Industrial product design.
AMS 2010 codes: 00A71

†Corresponding author.
Email address: zhangs8735@126.com

ISSN 2444-8656
https://doi.org/10.2478/amns.2023.2.01531

1 Introduction

Industrial product design in the national economy, especially in industrial production, has an extremely important position and role. Industrial product design management is the economy, technology and social management of the important combination of points. With the increasingly fierce competition in the market, some modern factories, in a few years after experiencing a big reshuffle, those who have enough product competitiveness of the manufacturers will stay in the market, and the old-fashioned enterprise will be eliminated. Modern industrial product design has been gradually diversified, and the future direction of product industrial design development is reflected in a number of levels, which will be people-oriented as the center, as far as possible, to meet people's needs [1]. With the development of science and technology, all industries have realized that technologization, especially for the industrial product design industry, to bring a positive impact is very far-reaching, and to a certain extent, the demand for industrial product design and design quality put forward more and more high requirements. In the context of the development of the new era, enterprises should grasp the opportunities for development and be ready to meet the challenges, deepen the reform of the product structure design work, conform to the trend of the times, and take the market demand as the benchmark, so that their core competitiveness can be improved [2].

Industrial product design refers to giving full play to the creativity of the designer, the use of existing human-relevant scientific and technological achievements for innovative ideas, and design with scientific, creative, novelty and practicality of practical activity. Industrial product design accelerates the transformation of economic growth mode and promotes the optimization and upgrading of industrial structure in an important way. Industrial product design has become one of the sources of competition in the manufacturing industry and the core power. Today's design is no longer limited to a specific form carrier but focuses on the overall system operation process of structural innovation [3-4]. The current situation of low technical capacity of industrial product design, relatively dispersed design resources, backward means of design services, and obsolete service mode, combined with the technical characteristics of product design oriented to the various links of the design chain, strengthen the construction of public service platform, has become an important issue to be resolved urgently to realize the industrial-technological innovation and accelerate the transformation of scientific and technological achievements [5-6].

This paper firstly constructs a general framework of industrial product design and service platform based on the KANO-AHP model and briefly analyzes its constituent components, co-design workshop, design resource manager, business department, and experimental integration for co-design. Secondly, the AHP analysis is utilized to establish the importance matrix of customer demand, and the importance degree of the engineering and technical characteristics of the product service system is obtained through the calculation of the importance matrix. Then, a quantitative KANO model is proposed to correct the importance degree of customer demand and determine the final importance degree of technical characteristics of product service system engineering. Finally, the platform that was designed is tested and evaluated based on user requirements and performance aspects. The results verify the feasibility as well as the effectiveness of the industrial product design and service platform, which can analyze the user needs, iterate the products better, maximize the user needs and improve user satisfaction under the limited capacity.

2 Relevant studies

With the rapid development of science and technology and the emergence of new technologies, the product upgrading speed is accelerated, and the life cycle is significantly shortened, resulting in increasingly fierce market competition. Literature [7] proposed a product configuration editor based on a visual interface of 3D software by utilizing the ball's product rapid design technology and parametric design technology, combining it with a PDM system, and verifying the effectiveness of the designed system through the experiments on the design of vehicle steering device. Literature [8] proposed a mapping design framework of additive manufacturing knowledge for industrial and product design and applied it to the design field of additive manufacturing, and proposed 9 future directions by summarizing the state of the art. Literature [9] considers data in the product development process as a fundamental means of monitoring the behavior of the product and the user towards optimization and discusses the challenges of data-driven design in early physical product design from both scientific and industrial perspectives. Literature [10] proposes the design of an edge cloud orchestration-driven solution based on cyber-physical systems and the industrial internet to fill the research gap in intelligent product service systems. Literature [11] argues that industrial design is an important aspect of human solutions to environmental problems and plays a key role in creating physical environments for human survival and lifestyles, and proposes a comprehensive green product evaluation system based on life cycle assessment that integrates industrial design knowledge.

In order to change the traditional industrial design mode, literature [12] introduced artificial intelligence technology in the process of industrial product design, established an industrial design service system based on artificial intelligence technology, and verified through theory and practice that the established system helps designers better analyze and apply complex data. Literature [13] proposed a closed-loop sustainable product design method for the circular economy based on the concepts of sustainable production and circular economy, and it was found through experiments that the method facilitates a holistic view of the product lifecycle, including the end of the "f" ife activity plan, leading to a permanent resource flow. Literature [14] describes the concept of a PSS model for knowledge representation in the design process of industrial product-service systems and proposes a knowledge-based approach to support the PSS design process. Literature [15] introduced a new design and engineering laboratory course in order to overcome the limitations between mechanical and industrial design, which was found to be effective in combining engineering practice with creative design through student feedback. Literature [16] describes a product design platform designed to support the development of customized products for traditional platform concepts, providing a coherent environment for heterogeneous design assets to support design activities and completed solutions.

3 Industrial product design and service platform based on KANO-AHP modeling

3.1 Construction of industrial product design and service platforms

Figure 1 shows the general framework of the industrial product design and service platform, which is aimed at designers, enterprises and customers, supported by the modern Internet, Internet of Things and logistics network, and based on industrial product manufacturing equipment, integrating design, production, manufacturing, promotion and consumption to form a new intelligent manufacturing industry model. The service platform system mainly consists of a collaborative design workshop, a design resource manager, a business department, and test integration parts for collaborative design. These are briefly described as follows:

1) Collaborative Design Platform

The objectives are to study the possibility of implementing a specific web application design and to measure the potential for collaborative development of design projects, which will lead to the development of two modules. The Collaborative Work module consists of a virtual space designed to enable different co-design participants to interact online during the design process, which allows participants to assist each other at different stages. The Design Process Support Module provides greater stability to the design and production process by creating a virtual space for product feasibility experiments.

2) Design Resource Manager

The concept is split into a monitoring module and a documentation module. The monitoring module performs search experiments using IAD technology to create a monitoring environment for the automated design process. The documentation module involves the research and development of documentation and user-defined standards on the theme of virtual machines, as well as the automated transfer of required information to other users in the industrial product design and service platform environment.

3) Business Unit

This module is designed to test and experiment with the product so that it supports the new services generated in the context of e-business applications, and this section is also designed in two parts. The Design Promotion module involves the validation of the technology and the provision of other features, a new generation of communities of practice, the creation of specialized social networks, merchant information, and product and service catalogs. The Business Opportunities module includes other design-related businesses generated through experiments.

4) Integration of experiments for co-design

In this module, the paper experiments with collaborative tools in open resource web environments to improve and simplify activities or tasks related to the management of product design, the conceptualization of products by acting as a service to the company in the face of marketing, which designers provide in an enactable environment.

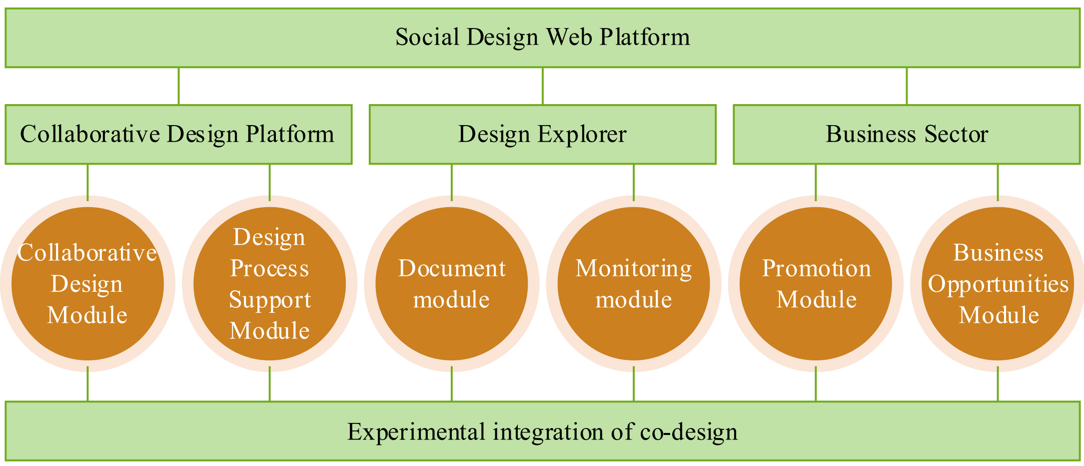


Figure 1. Overall framework of industrial product design and service platform

3.2 KANO-AHP modeling

3.2.1 KANO model

The KANO model was formally proposed by Professor Norioaki Kano of the Tokyo Institute of Technology in 1984 to screen, classify, and rank user needs. The KANO model breaks the traditional unilateral cognition of user needs and examines the satisfaction of users from the positive and negative aspects of satisfying a certain need and those who do not meet a certain need so as to establish a nonlinear relationship between the degree of demand and user satisfaction [17-18]. Figure 2 shows the KANO model, which divides user needs into necessary needs, desired needs, charm needs, undifferentiated needs, and reverse needs.

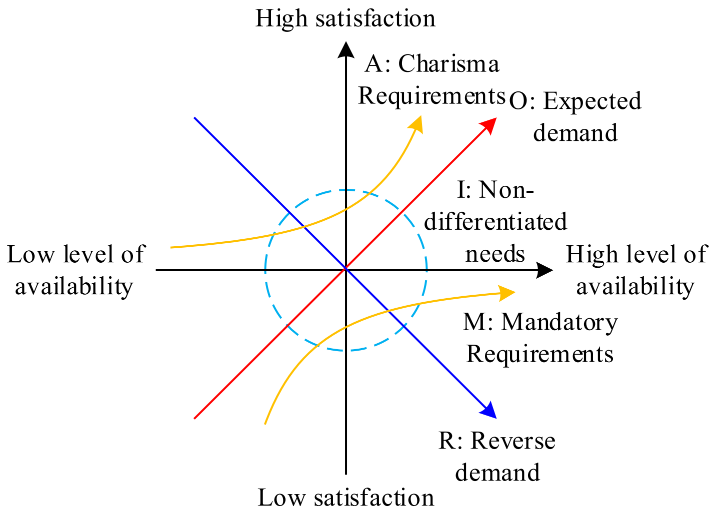


Figure 2. KANO model

1) Necessary needs

These are the basic needs of users and constitute the first level of user needs. When such needs are not met, user satisfaction will drop sharply, which greatly leads to users giving up this product or service, and when such needs are met or optimized, user satisfaction will not increase.

2) Expected demand

The second level of user needs is the needs of the user. The degree of satisfaction of the expected demand is directly proportional to the user satisfaction. The higher the degree of satisfaction of the demand, the higher the user satisfaction. Such demand is often clearly understood by the user and can be accurately described.

3) Charm demand

Also known as excitement needs is the third level of user needs. This kind of demand for the user's potential needs, to meet the unexpected new experience will be achieved, bring surprise to the user, and user satisfaction will rise sharply, when not met, user satisfaction will not fall, because users often do not realize these needs.

4) No difference demand

This demand will not have an impact on user satisfaction, whether it is satisfied or not.

5) Reverse demand

The satisfaction of this demand will cause a decrease in user satisfaction when it is satisfied but will increase user satisfaction when it is not satisfied.

3.2.2 Modeling Approach for AHP Analysis

The most important aspect of the hierarchical analysis method in the analysis of decision-making objectives is the construction of a hierarchical analysis model [19]. From the bottom to the top are the program level, the criterion level and the goal level. The number of layers in the hierarchical model is related to the complexity of the problem, as well as the level of detail of the analysis. And in general the number of layers is not limited, but the number of elements dominated by each element in each layer is generally not more than nine. This is because the domination of too many elements will bring difficulties to the two-two two-comparison judgment.

Hierarchical analysis provides a new, concise and practical modeling method for decision making and ranking of such problems. Modeling using hierarchical analysis, the general steps are to establish a hierarchical model of recursive order, construct all the judgment matrices in each level, hierarchical single sorting and consistency test, and hierarchical total sorting and consistency test. The specific method steps are as follows:

1) Construct judgment matrix

Any systematic analysis should be based on information, and the information basis of the AHP analysis method mainly comes from the expert group's two-by-two comparison and judgment of the elements of each level, and these judgments are expressed in numerical values, and finally shown in the form of a matrix, which is the so-called judgment matrix of the degree of importance. The judgment matrix constructed by the expert group indicates the relative importance of an element at the upper level to the relevant element at the lower level, as well as the relative importance of different indicators between the same levels.

For n element, a two-by-two comparison of the judgment matrix $C=\left(C_{ij}\right)_{n\times n}$. Where C_{ij} denotes the factor i and factor j relative to the target importance value. In general, the form of the constructed judgment matrix is shown in Table 1.

Table 1. Judgment matrix

B_k	C_1	C_2	Λ	C_n
C_1	C_{11}	C_{12}	Λ	C_{1n}
C_2	C_{21}	C_{22}	Λ	C_{2n}
M	M	M		M
C_n	C_{n1}	C_{n2}		C_{nn}

Clearly matrix C has the property that:

$$C_{ij}>0;C_{ij}=1/C_{ji}(i\neq j);C_{ii}=1(i,j=1,2\ldots n) \tag{1}$$

We call such matrices C positive and negative matrices. The positive and negative matrix C satisfying $C_{ij}\cdot C_{jk}=C_{ik}$ is called the consistency matrix. In hierarchical analysis, in order to quantify decision judgments and form numerical judgment matrices, the 1-9 scale suggested by Saaty is usually used.

From a psychological point of view, too much grading will exceed people's ability to make judgments, which increases the difficulty of judgments and is easy to causes data confusion and untruthfulness as a result. Saaty and other scholars used experimental methods to compare the correctness of judgments made by people under different scales, and the results of the experiments also showed that the scale of 19 scales is the most appropriate.

Finally, it should be noted that $n(n-1)/2$ two-by-two judgments are generally necessary. Making $n(n-1)/2$ comparisons can provide more information and lead to the derivation of a reasonable ranking through repeated comparisons from a variety of perspectives.

2) Hierarchical single ranking and consistency test

The judgment matrix A and the largest eigenvalue $\lambda_{\max}$ eigenvector W corresponds to the same level of the corresponding factors after the normalization operation for the previous level of the relative importance of a factor in the ranking of the weights, this process is called hierarchical single sort.

(1) Calculation of the largest eigenroot of the judgment matrix

Theoretically, the computation of hierarchical single ordering can be reduced to the problem of computing the maximum eigenroot of the judgment matrix and its eigenvectors. The calculation method is as follows:

The first step is to calculate the product M_i of the row elements of the judgment matrix with the expression:

$$M_i = \prod_{j=1}^{n} a_{ij} i = 1,2,\ldots,n \tag{2}$$

In the second step, compute the expression for the n nd power root of M_i for $\overline{W_i}$:

$$\overline{W_i} = \sqrt[n]{M_i} \tag{3}$$

In the third step, the vector $\overline{W} = \left[\overline{W}_1, \overline{W}_2, \ldots, \overline{W}_n\right]^T$ is regularized with the processing equation:

$$W_i = \frac{\overline{W_i}}{\sum_{j=1}^{n} \overline{W_j}} \tag{4}$$

Then $W = \left[W_1, W_2, \ldots, W_n\right]^T$ is the desired eigenvector.

In the fourth step, the expression for the largest eigenroot $\lambda_{\max}$ of the judgment matrix is computed as:

$$\lambda_{\max} = \sum_{i=1}^{n} \frac{(AW)_i}{nW_i} \tag{5}$$

Where $(AW)_i$ denotes the i rd element of vector AW.

(2) Consistency test of judgment matrix

A consistency test is required for hierarchical single ordering and hierarchical total ordering. A correct judgment matrix importance ranking is a certain logical law. For example, if the industrial environment is more important than the industrial technology, and logically, the industrial technology should be more important than the industrial environment, the judgment matrix violates the consistency criterion and is logically unreasonable. Therefore, in practice, the judgment matrix is required to meet the general consistency of the consistency test. The steps of consistency test are as follows:

The first step is to calculate the expression of the consistency index CI as:

$$CI = \frac{\lambda_{\max} - n}{n-1} \tag{6}$$

(3) In the second step, find the corresponding average random consistency indicator RI.

(4) Calculate the expression for the consistency ratio CR as:

$$CR = \frac{CI}{RI} \tag{7}$$

When $CR < 0.10$, the consistency of the judgment matrix is considered acceptable, otherwise the judgment matrix should be appropriately corrected.

3) Hierarchical total ordering and consistency test

Above, we get a vector of weights of a set of elements on an element in its upper level. We ultimately want to get the ranking weights of each element, especially the lowest level of each program for the target, so as to carry out program selection. By calculating the hierarchical model layer by layer from top to bottom, the relative importance of the lowest layer's factors to the target layer, i.e., the total hierarchical ranking, can be calculated. In other words, the overall hierarchical ranking is for the highest level.

Let the previous level contain $A_1,\ldots A_m$ a total of m factors, their total ordering weights are $a_1,\ldots a_m$. Let the next level contain n factors $B_1,\ldots B_n$, their hierarchical single ordering weights on A_j are $b_{1j},\ldots b_{nj}$. First find the weights of the factors in level B on the total goal, i.e., find the hierarchical total ordering weights of the factors in level B. $b_1,\ldots b_n$ is calculated as:

$$b_i = \sum_{j=1}^{m} b_{ij} a_j, i = 1,\ldots,n \tag{8}$$

3.3 Requirements Importance Determination Methodology

3.3.1 Methodology for determining the importance of customer needs

The Product Service System Engineering Technical Characterization Importance Matrix W can be expressed as:

$$W = \begin{bmatrix} W_{11} & 0 & 0 \\ W_{21} & W_{22} & W_{23} \\ W_{31} & W_{32} & W_{33} \end{bmatrix} \tag{9}$$

Where, W_{11} is a vector of customer demand importance weights. W_{21} and W_{31} represent the mapping relationships between customer demand and product engineering characteristics and service engineering characteristics, respectively. W_{22} and W_{33} are the autocorrelations of the product engineering characteristics and service engineering characteristics, respectively. W_{23} and W_{32} are the influence relationships between product engineering characteristics and service engineering characteristics, respectively.

The steps for calculating the initial importance of technical characteristics of product service system engineering are as follows:

In the first step, for the customer demand elements, consider the customer demand autocorrelation, establish the customer demand importance comparison matrix, and calculate the customer demand importance weight vector W_{11}.

In the second step, assuming that there is no autocorrelation between the engineering characteristics of the product-service systems, a two-by-two comparison matrix of customer requirements and technical characteristics is established, and the obtained weight vectors of technical characteristics of each group of product-service systems, W_{21} and W_{31}, are calculated.

In the third step, for the internal autocorrelation of the technical characteristics of the product-service system, the importance weight vectors W_{22} and W_{33} are calculated for the technical characteristics of the product and the technical characteristics of the service, respectively.

In the fourth step, the weight vectors W_{23} and W_{32} are calculated for the importance vectors of product and service technical characteristics with respect to the interrelated effects of the technical characteristics of the product-service system.

How to solve the two-by-two comparison matrix is a key issue in the process of determining the importance of technical characteristics of product-service system engineering. Assuming that m expert, the importance matrix is established for n demand elements, and different decision weight vectors $C = \{C1, C2, \cdots, Cm\}$ are assigned to different experts according to their experience and credibility, where $C_k \in [0,1]$. The result of the kth expert's evaluation of the relative importance degree of element i compared to element j is expressed as a triangular fuzzy number:

$$a_{ij}^k = \left(a_{ijs}^k, a_{ijg}^k, a_{iju}^k\right) \tag{10}$$

Accordingly, the fuzzy two-by-two comparison matrix given by the k st expert Table A^k can be expressed as:

$$A^k = \begin{bmatrix} 1 & \cdots & \left(a_{1ns}^k, a_{1ng}^k, a_{inu}^k\right) \\ \cdot & \ddots & \vdots \\ a_{n1s}^k, a_{n1g}^k, a_{n1u}^k & \cdots & 1 \end{bmatrix} \tag{11}$$

One of the $i \neq j$ hour:

$$\left(a_{jis}^k, a_{jig}^k, a_{jiu}^k\right) = \left(1/a_{ijs}^k , 1/a_{ijg}^k , 1/a_{iju}^k \right) \tag{12}$$

When $i = j$:

$$\left(a_{ijs}^k, a_{ijg}^k, a_{iju}^k\right) = (1,1,1) \tag{13}$$

Using the least logarithmic squares method, the fuzzy two-by-two comparison matrix A^k triangular fuzzy number weight vector W^k, W^k can be expressed as:

$$\begin{aligned} w^k &= \left(w_1^k, w_2^k, \ldots\ldots, w_n^k\right)^T \\ &= \left(\left(w_{1s}^k, w_{1g}^k, w_{1u}^k\right), \left(w_{2s}^k, w_{2g}^k, w_{2u}^k\right), \ldots\ldots, \left(w_{ns}^k, w_{ng}^k, w_{nu}^k\right)\right)^T \end{aligned} \tag{14}$$

Among them:

$$w_{is}^k \leq w_{ig}^k \leq w_{iu}^k \tag{15}$$

After comparing the importance matrix A^k and the fuzzy weight vectors of each element within the matrix based on two-by-two comparison of the elements by each expert, it is necessary to integrate all the expert weight vectors to obtain a more reasonable unified weight vector. Here the weighted average method is used to solve the integration vector W_i with all weight vectors W_i^k, and the solution formula is:

$$w_i = \left(w_{is} + w_{ig} + w_{iu}\right)/3 = C_k \left(w_{is}^k + w_{ig}^k + w_{iu}^k\right)/3k \tag{16}$$

With the above methodology, the weight vectors of each set of weights that need to be calculated in the 4 steps of the Product Service System Engineering Technical Characteristics Importance Matrix can be obtained.

3.3.2 A method for correcting the importance of customer needs based on the quantitative KANO model

Establishing the customer demand importance matrix and obtaining the product service system engineering technical characteristic importance degree through the importance degree matrix calculation only considers the customer's importance degree for the product and service technical characteristic but does not consider the customer's satisfaction degree for the product and service technical characteristic. For this reason, this section proposes a quantitative KANO model to correct the customer demand importance degree and determine the final importance degree of the technical characteristics of product service system engineering.

1) Construction of quantitative KANO model

Assumption T represents a set of J interviewed customers, i.e., $T \equiv \{t_j \mid j = 1, 2, \ldots\ldots, J\}$, t_j represents the j th interviewed customer. Assumption F represents a set of I product-service engineering attributes, i.e., $F \equiv \{f_i \mid i = 1, 2, \ldots\ldots, I\}$ and f_i represent the i th product-service engineering attribute. The value of the j th customer's evaluation of the i th product service engineering technical characteristic attribute can be expressed as $e_{ij} = (x_{ij}, y_{ij})$, where x_{ij} is the satisfaction evaluation of the customer j when the i th product service engineering technical characteristic attribute is not provided, and y_{ij} is the satisfaction evaluation of the customer j when the i th product service engineering technical characteristic attribute is provided. The values of x_{ij} and y_{ij} can be obtained by Kano model questionnaire. The average satisfaction and average dissatisfaction of customers for the i rd product service engineering technical characteristic attribute can be obtained by questionnaire survey of J customers, respectively:

$$\overline{X}_i = \frac{1}{J}\sum_{j=1}^{J} x_{ij} \text{ and } \overline{Y}_i = \frac{1}{J}\sum_{j=1}^{J} y_{ij} \tag{17}$$

The two-dimensional distribution of attribute satisfaction was established using $\overline{X}_i$ and $\overline{Y}_i$ as shown in Fig. 3, where the horizontal coordinate represents the dissatisfaction value and the vertical coordinate represents the satisfaction value.

As shown in Fig. 3, the product service engineering technical characteristic attribute f_i can be described in the form of a two-dimensional vector as $f_i \sim \bar{r}_i \equiv (r_i, \alpha_i)$, where $r_i = |\bar{r}_i| = \sqrt{\overline{X}_i^2 + \overline{Y}_i^2}$, is the moment of vector $\bar{r}$, which indicates the degree of importance of product service engineering technical characteristic f_i to the customer, and becomes the Kano importance indicator. $\alpha_i = \tan^{-1}\left(\overline{Y}_i / \overline{X}_i\right)$, is the angle between vector $\bar{r}_1$ and the horizontal coordinate axis, which determines the relative level between the customer's satisfaction/dissatisfaction with the product service engineering technical attribute f_i, and is called the Kano satisfaction indicator.

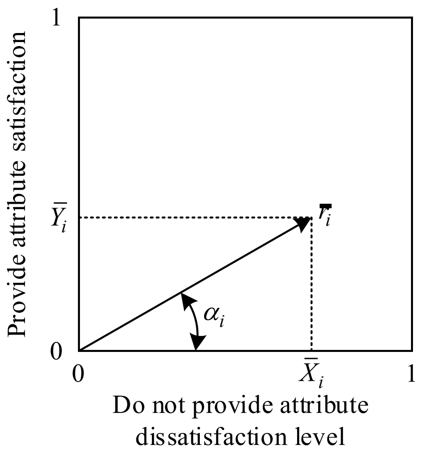


Figure 3. Two-dimensional distribution of attribute satisfaction

2) Determination of the final importance of customer needs based on the quantitative KANO model

The increased ratio of basic quality attributes is smaller than the increased ratio of customer satisfaction, the increased ratio of desired quality attributes is linearly related to the increased ratio of user satisfaction, and the increased ratio of excited quality attributes is larger than the increased ratio of customer satisfaction. Therefore, these 3 relationships can be expressed as:

(1) Basic quality attributes $\Delta S / S < \Delta p / p$

(2) Expected quality attributes $\Delta S / S = \Delta p / p$

(3) Excitement quality attribute $\Delta S / S > \Delta p / p$

Simplification of the above 3 relationships yields the expression formula as:

$$\Delta S / S = k \Delta p / p \tag{18}$$

For the basic attribute, $0 < k < 1$. For the desired attribute, $k = 1$. For the excited attribute, $k > 1$. Equation (18) can be further converted to:

$$S = cp^k \tag{19}$$

Here, c is a constant. Let S_0 and p_0 be the current customer satisfaction and product service engineering technical characteristics, and S_1 and p_1 be the target values of customer satisfaction and product service engineering technical characteristics, we can get $S_0 = cp_o^k$ and $S_1 = cp_1^k$. We can derive the expressions as:

$$\frac{S_1}{S_o} = \frac{cp_1^k}{cp_o^k} = \left(\frac{p_1}{p_0}\right)^k \tag{20}$$

Further the expression can be derived as:

$$IR_{adj} = \left(IR_0\right)^{1/k} \tag{21}$$

Where IR_0 is the initial improvement rate, which indicates the expected rate of improvement of customer satisfaction, and can be determined by calculating the ratio of the desired value of the product service engineering technical characteristic attribute to the existing value. IR_{adj} is the modified improvement rate, which indicates the improvement rate of upgrading the attributes of the product service engineering technical characteristics in order to achieve the expected customer satisfaction. The modified improvement rate is multiplied by the initial importance of the product service engineering technical attributes to obtain the final importance of customer demand.

The correction process of customer demand final importance based on the quantitative Kano model is shown in Fig. 4.

In the first step, the Kano satisfaction index α_i is calculated according to the principle of the quantitative Kano model and its tangent value $\tan\alpha_i$ is found.

The second step is to determine the improvement coefficient. Compare the ratio of the ideal value of the product service engineering and technical characteristics attributes to the existing value two by two to determine the improvement coefficient.

The third step is to correct the improvement coefficient. Make $k = \tan\alpha_i$ and substitute k into Equation (21) to get the modified improvement rate.

Step 4, calculate the final customer demand importance. The product of the corrected improvement coefficient and the initial importance is the final product service engineering technology characteristic importance.

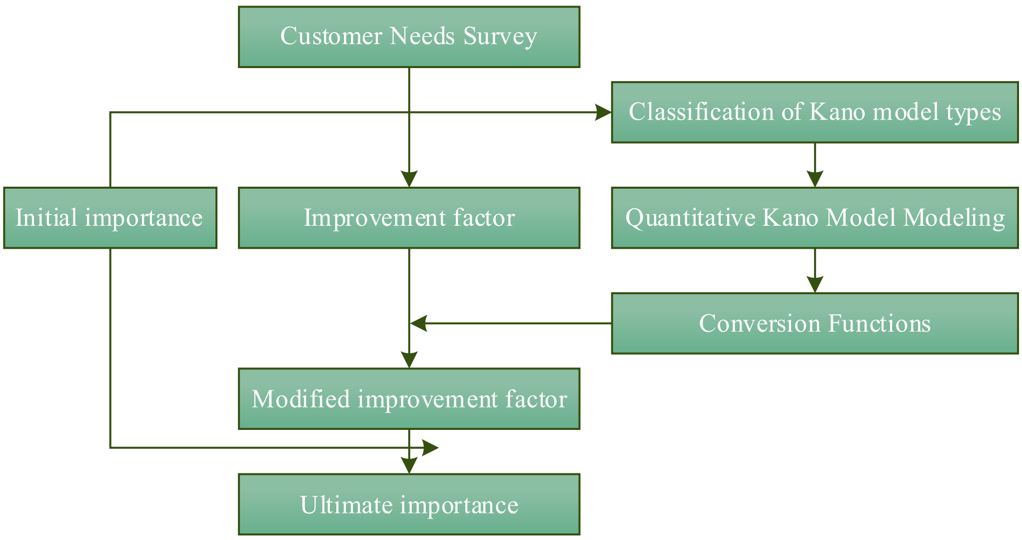


Figure 4. Process of correcting the ultimate importance of customer needs

4 Industrial product design and service platform testing and analysis

4.1 Analysis of platform user requirements

In order to verify the effectiveness of the KANO-AHP model and design the KANO answer sheet for industrial product design, user needs were investigated. Taking small and medium-sized enterprises in G city as the research object, we analyze the users through network research, data analysis and other methods and synthesize the local policy conditions and geographical conditions to obtain user characteristics. Combined with SWOT analysis and group brainstorming methods, we analyzed the advantages, difficulties and points to be improved in the process of design activities and innovation, which served as the basis for user analysis. Through the establishment of the regional user demand research interview form, the enterprises with regional characteristics were interviewed to further explore the user demand. In this study, the interview subjects are selected from enterprises and research institutions. The types of enterprises mainly include scientific and technological research, production and research and development, design and service, etc. The user types are selected as broadly as possible for the interview to ensure that the results of the interviews are accurate and effective. Table 2 shows the summary of user demand attributes, where A-DSI stands for charismatic demand, desired demand, essential demand, undifferentiated demand, user satisfaction coefficient, and user dissatisfaction coefficient, respectively. From the data in the table, it can be seen that the value of charismatic demand for marketing, market feedback, property right construction and branding are all 19.27, and the expected demand for creative support, design service and financial preparation is the same, and the necessary demand for human support, product testing, market feedback and property right construction are all 21.44. The data illustrate that between the demand items for industrial product design and service platforms analyzed in this study, the KANO- AHP model is more effective in distinguishing the attributes of the demand items, and the preliminary analysis results show that there is no obvious relationship between the above demands/services and satisfaction.

Table 2. User requirements attribute summary

Encoding	Demand content	A/%	O/%	M/%	I/%	SI	DSI
1	Industry information	16.45	17.16	36.45	21.45	0.38	-0.59
2	Government dynamics	15.02	20.72	35.00	20.73	0.39	-0.62
3	Design material	16.41	21.45	25.00	27.88	0.43	-0.50
4	Event dynamics	12.14	30.72	23.54	25.02	0.47	-0.59
5	Design research	15.01	15.71	23.54	36.44	0.33	-0.60
6	Human support	35.72	17.15	21.44	17.16	0.57	-0.43
7	Expert support	22.88	35.00	17.15	15.17	0.63	-0.58
8	Creative support	17.14	22.16	18.54	33.58	0.45	-0.44
9	Design services	32.88	22.16	23.58	12.87	0.62	-0.51
10	Collaborative design	17.14	20.81	22.88	30.70	0.43	-0.47
11	Scheme evaluation	12.85	10.72	25.71	42.15	0.27	-0.41
12	Sample making	24.30	24.29	24.29	18.59	0.52	-0.52
13	Product testing	23.56	22.87	22.14	22.87	0.50	-0.48
14	Benefit forecast	18.54	14.30	27.84	30.73	0.36	-0.45
15	Production support	23.57	20.02	22.86	25.02	0.48	-0.46
16	Fund raising	27.84	22.16	20.70	20.01	0.55	-0.46
17	Marketing	19.27	10.73	22.13	39.27	0.34	-0.37
18	Market feedback	19.27	15.70	21.44	35.00	0.39	-0.43
19	Property right construction	19.27	27.16	21.44	23.58	0.52	-0.54
20	Brand building	19.27	21.45	30.02	20.70	0.44	-0.56
21	Online review	22.85	22.85	18.54	27.16	0.51	-0.46

KANO-AHP model, when the frequency of demand attributes is similar or the same, the results of the division of demand items are not clear enough, so with the help of influence coefficients, Better and Worse classifications are used to divide the results even further, and both Better and Worse are used to determine the degree of sensitivity of the user to changes in the level of demand/service. The Better-Worse coefficient classification results are presented in the form of a scatterplot, which enables a clearer view of the division of the attributes of the demand/service. The scatterplot is made by crossing Worse as the vertical coordinate, Better as the horizontal coordinate and Mean (0.0456,-0.4985) as the center point. Figure 5 shows the Better-Worse coefficient classification results. There are 5 items of charismatic needs in the first quadrant, 5 items of aspirational needs in the second quadrant, 4 items of essential needs in the third quadrant, and 5 items of undifferentiated needs in the fourth quadrant, in which design material is on the dividing line between essential and undifferentiated needs, and creative support is on the dividing line between charismatic and undifferentiated needs. Using Better-Worse coefficient classification, the classification results underwent an I-A-O-M transformation. The analysis shows that the KANO-AHP model classifies the attributes of the needs and services of industrial product design and services, determines the different attribute modules, and determines the positive and negative aspects of the different needs and services on user satisfaction.

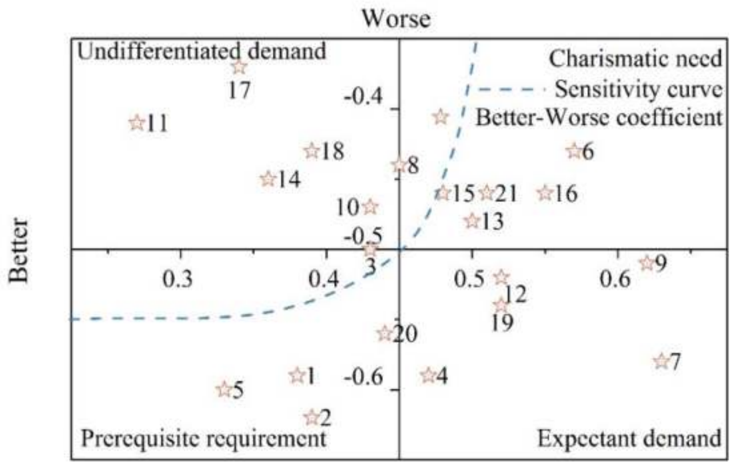


Figure 5. Classification results of Better-Worse coefficients

In order to prioritize the requirements of the industrial product design and service platform, satisfaction sensitivity analysis is introduced with reference to Zhao Ping's method of determining optimized requirements. Satisfaction sensitivity analysis can determine the degree of change in user satisfaction levels for different requirements/services and, based on this, prioritize the direction of improvement that can enhance user satisfaction with the product. The main method is based on the scatterplot. Through the scatterplot origin to the cross point of the reference line that is the distance from the mean point for the arc, draw a quarter arc, the arc for the sensitive line, as shown in Figure 5. The farther the distance from the origin, the greater the user satisfaction sensitivity. The more priority needs to be given to the demand located on the right side of the sensitive line for the focus of attention to the demand. Table 3 illustrates the sensitivity of industrial product design and service platform to demand and service.

From the sensitivity analysis, it can be seen that there are a total of 13 improvement elements in the 21 service demand items of the industrial product design and service platform previously sorted out. Expert support, manpower support, and fundraising are the top three of the improvement elements, with sensitivities of 0.107, 0.103, and 0.100, respectively, which shows that at present, in terms of data collection, the problem of collection of tripartite data and uploading of historical data are the primary problems that users are eager to solve at present. In summary, the above data indicates that industrial product design and service platforms can refer to the above order of improvement, combined with their own needs, in the case of limited production capacity, better iteration of the product to maximize the user's needs and enhance user satisfaction.

Table 3. Industrial product design and service platform needs/service sensitivity

Encoding	Demand/Service	Sensibility	Ranking	Classification result
7	Expert support	0.107	1	A
6	Human support	0.103	2	O
16	Fund raising	0.100	3	A
9	Design services	0.099	4	O
12	Sample making	0.091	5	O
21	Online review	0.087	6	A
19	Property right construction	0.084	7	O
2	Government dynamics	0.078	8	M
1	Industry information	0.079	9	M
13	Product testing	0.077	10	M
3	Design material	0.073	11	M
4	Event dynamics	0.071	12	O
20	Brand building	0.068	13	M

4.2 Platform Performance Testing

4.2.1 Request/response service analysis

In order to validate the effectiveness and operational performance of the test platform, this study conducts performance testing for multiple interfaces of HTTP services of the industrial product design and service platform. At two levels, testing and analysis are conducted. On the one hand, for a single interface, the average response time and RPS of the interface are used as reference indicators to observe the service level and performance bottleneck of the interface under different loads. On the other hand, the number of HTTP service load balancing is adjusted, and the Redis cache database is configured to observe the impact of different server-side system configurations on the interface load performance under the same load.

1) Analysis of interface performance

Taking the common GET-type interface for obtaining user information in HTTP service as an example, when the number of load balancing is set to 1, and Redis cache is enabled, the curve of the number of requests processed per second and the average response time obtained from the test with the change of concurrent simulated users is shown in Figure 6. When the number of simulated users is less than 8000, the average time for the server to respond to requests is basically unchanged, maintained at 10ms, and all requests can be processed in a timely manner. Before the number of simulated users reaches 10000, the response time slightly increases as the number of users increases, and the number of requests processed per second increases linearly. When the number of simulated users exceeds 10000, the average response time of the request increases abruptly, and the number of requests processed per second decreases instead of increasing, indicating that the server reaches a performance bottleneck at this time, and the maximum number of requests processed per second supported by the interface is around 1700. At the end of the curve of the number of requests per second with concurrent simulation of the user changes, the response time curve changes seem to be smooth. In fact, it is infinitely close to the HTTP request timeout 10s upper limit. The upper limit of the time you did not get a response to the request is not recorded in the calculation of the average response time. Response time at the end of the curve of the average response time with the concurrent simulation of user changes, the average number of requests per second processing has dropped and risen, but they are lower than the maximum RPS value of 10,000, this stage belongs to the service in the test pressure higher than the maximum load, the response-ability is not stable performance.

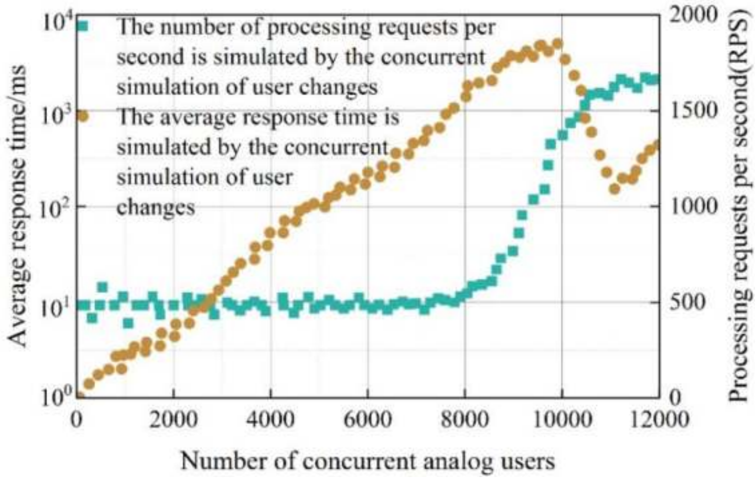


Figure 6. The response time changes of the request number of requests per second

2) Analysis of the server configuration

During the testing process, this paper for the same GET type interface, respectively, test set Redis cache data or not set the case, HTTP service load balancing number of 1, 2, 4 when the interface performance, the average response time change curve in the six cases shown in Figure 7. Obviously, for the same cache configuration, the more the number of load balances, the higher the maximum load that the system can support, and when the system is not cached, the number of concurrent users exceeds 6000, and its average response time is more than 103 ms. Interfaces with caches have a much better performance than interfaces without caches for the same number of load balances. For the same number of simulated users, even under normal load, when the number of load balancing with cache, the maximum number of concurrent users can reach 20,000, and the average response time is about 103ms, the response time of the interface with cache is smaller than that of the interface without cache. The maximum RPS of the interface obtained from the test can lead to the same conclusion. For the tested GET-type HTTP interface, the more load-balanced services are configured, the more data caching is configured, which can obviously lead to performance improvement. The above experiments illustrate that the platform built in this paper can automatically perform multiple rounds of load testing on a batch of HTTP interface scripts, obtaining performance data and load bottlenecks for each interface that change with the growth of concurrent users. The effectiveness of the performance testing system for HTTP services is verified through testing practices on real platform services.

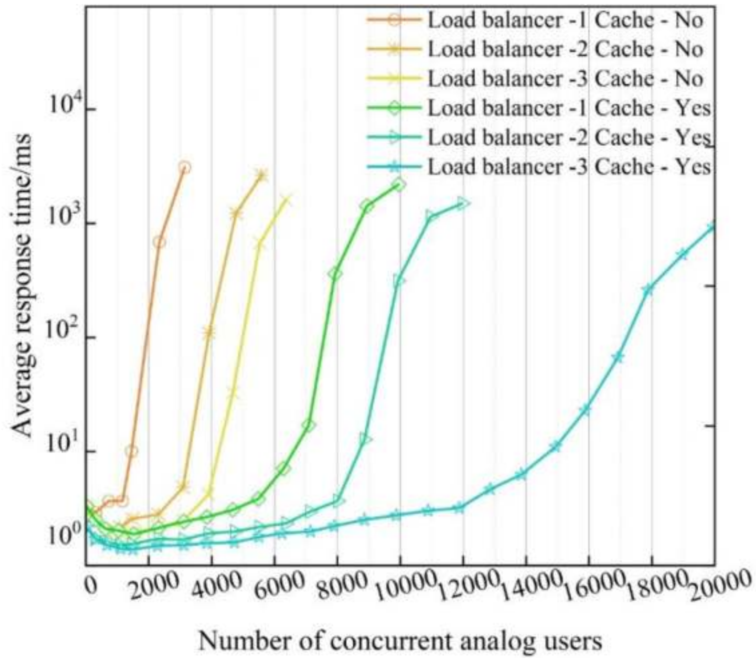


Figure 7. Comparison of the average response time curves of interfaces in different configurations

4.2.2 Matching efficiency analysis

The collaborative task decomposition and allocation process for industrial product design is used as an experimental object to verify the efficiency of the platform designed in this paper. The modular task reorganization and allocation method used in the platform of this paper is compared with the traditional task decomposition and allocation method, and the decomposed tasks are directly assigned to virtual resources. The whole experimental process simulates the service platform environment, and in the case PCs are used to simulate off-site distributed virtual resources, the tasks and virtual resources are centrally managed by workstations, and the virtual resources collaborate to complete the modular reorganization and allocation of tasks in a network-connected environment. The two methods were programmed using MATLAB and compared and analyzed using matching period, service quality, and on-time task completion rate as objective functions. Where the variation rate is 0.04, and the crossover rate is 0.7, 50 operations are performed. The value of the objective function for experimental convergence is shown in Figure 8, and the number of iterations for experimental convergence is shown in Figure 9.

As can be seen from Fig. 8, both methods are feasible in solving collaborative task decomposition and assignment and converge to the same objective function value in 50 experiments. The optimal objective function value of the modular task reorganization and allocation method used in this paper is 4.1, and the optimal objective function value of the traditional task decomposition and allocation method is 2.95. From the optimal value of the objective function, it can be seen that the task allocation model of the platform proposed in this paper makes a better match between modular tasks and virtual resources, and the optimal combination of virtual resources can be found in the virtual resource candidate set.

As can be seen from Fig. 9, the number of convergence iterations of the traditional method fluctuates greatly, with a magnitude range of [8.12,108.40], while the modular task reorganization and allocation method used in this paper's platform has less fluctuation in the number of convergence iterations, with a magnitude range of [4.06,25.09]. Compared with the traditional method, the modular task reorganization method can reduce the difficulty of solving task resource matching in the task allocation session, accelerate the model solving speed, and reduce the consumption of computing power of the industrial design cloud service platform, which effectively improves the matching efficiency in the process of sub-task and service resource allocation.

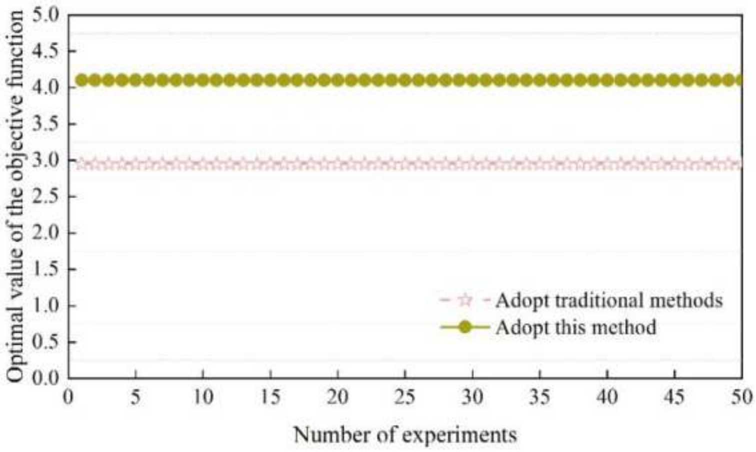


Figure 8. Value of the objective function of experimental convergence

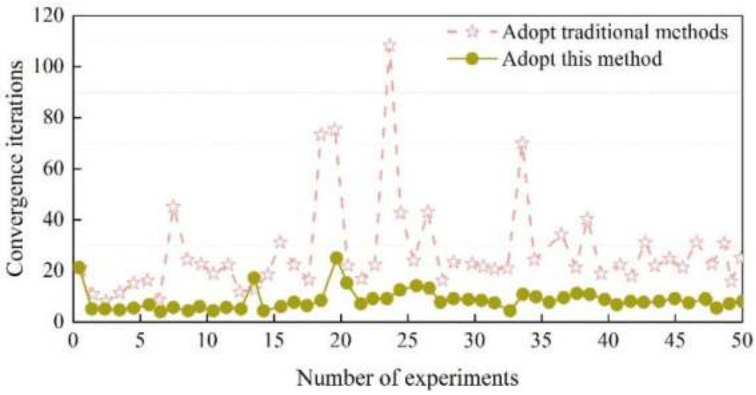


Figure 9. Number of iterations of experimental convergence

5 Conclusion

While ensuring the realization of its material functions, industrial product design should also fully consider all human-related factors, such as the psychological and physiological needs of users, and comprehensively satisfy people's needs for both the material and spiritual functions of products. Therefore, this paper constructs an industrial product design and service platform based on the KANO-AHP model, verifies the feasibility of the constructed platform through the platform user demand analysis and platform performance test, and draws conclusions:

1) As far as the platform user demand analysis is concerned, expert support, manpower support and fundraising in the service demand item of the industrial product design and service platform are the top three of the improvement elements, with sensitivities of 0.107, 0.103, and 0.100, respectively, which shows that at present in the aspect of data collection, the problem of collection of tripartite data and uploading of historical data are the primary problems that users are eager to solve at present.

2) As far as the platform performance test analysis is concerned, for the same cache configuration, the more the number of load balancing, the higher the maximum load that the system can

support, and when the system does not have a cache, the number of concurrent users exceeds 6000, and its average response time is more than 103ms. Compared with the traditional task decomposition and allocation method, the optimal value of the converged objective function of the modular task reorganization and allocation method adopted by the platform in this paper is improved by 1.15. It can be seen that the task allocation model of the proposed platform in this paper makes a better match between modular tasks and virtual resources, and it can find the optimal combination of virtual resources in the candidate set of virtual resources.

Funding:

This research was supported by the 2021 Zhejiang Province Philosophy and Social Sciences Planning Project: “Zhejiang Province Social Science Planning Project Results” (21NDQN286YB) “Research on the Creative Design and Network Cooperation of Bamboo Art Youth in Zhejiang and Taiwan Based on the Innovation Ecosystem”.

References

[1] He, F. (2017). Industrial product graphic design based on visual communication concept. Acta Technica CSAV (Ceskoslovensk Akademie Ved), 62(1), 269-278.

[2] Kim, K. M., & Lee, K. P. (2016). Collaborative product design processes of industrial design and engineering design in consumer product companies. Design Studies, 46(sep.), 226-260.

[3] Guini, F., Barkany, A. E., Jabri, A., & Lrhirane, E. H. (2018). An approach for the evaluation of a product’s process planning during the design phase through a group multi-criteria decision-making. International Journal of Engineering Research in Africa, 38, 154-162.

[4] Cai, Y., Wang, Z., He, P., Lu, Z., & Tang, J. (2017). The industrial network system design based on profinet1. Acta Technica CSAV (Ceskoslovensk Akademie Ved), 62(1), 21-31.

[5] Hélose Ragelle a, B, S. R., C, E. A. G., A, P. D. W., C, M. W. T., & Grégoire Schwach b, et al. (2021). Additive manufacturing in drug delivery: innovative drug product design and opportunities for industrial application. Advanced drug delivery reviews, 178, 113990.

[6] Renaud, M. A. N. (2019). Product manual elaboration in product design phases: behavioral and functional analysis based on user experience. International Journal of Industrial Ergonomics, 71.

[7] Liu, F. (2020). Fast industrial product design method and its application based on 3d cad system. Computer-Aided Design and Applications, 18(S3), 118-128.

[8] Pradel, R. M. J. (2018). A framework for mapping design for additive manufacturing knowledge for industrial and product design. Journal of Engineering Design, 29(4a6).

[9] Briard, T., Jean, C., Aoussat, A., & Veron, P. (2023). Challenges for data-driven design in early physical product design: a scientific and industrial perspective. Computers in Industry.

[10] Liu, B., Zhang, Y., Zhang, G., & Zheng, P. (2019). Edge-cloud orchestration driven industrial smart product-service systems solution design based on cps and iiot. Advanced Engineering Informatics, 42, 100984.

[11] Zhou, P. (2019). Design and implementation of paper product industrial design management system under the framework of green lca theory. Paper Asia, 2(3), 166-171.

[12] Zhang, F. (2022). Design and implementation of industrial design and transformation system based on artificial intelligence technology. Mathematical Problems in Engineering, 2022.

[13] Hapuwatte, B. M., & Jawahir, I. S. (2021). Closed-loop sustainable product design for circular economy. Journal of Industrial Ecology.

[14] Belkadi, F., Zhang, Y., Irazusta, L. U., Maleki, E., Bernard, A., & Koukas, S. (2017). Pss pattern concept for knowledge representation in design process of industrial product-service systems. Procedia Cirp, 60, 428-433.

[15] Katz, R., & Talmi, I. (2017). Teaching industrial design in mechanical engineering: a laboratory for design and engineering. International Journal of Engineering Education, 33(2A), 672-679.

[16] Samuel Andr, Fredrik Elgh, Joel Johansson, & Roland Stolt. (2017). The design platform – a coherent platform description of heterogeneous design assets for suppliers of highly customised systems. Journal of Engineering Design.

[17] Li, M., & Zhang, J. (2021). Integrating kano model, ahp, and qfd methods for new product development based on text mining, intuitionistic fuzzy sets, and customers satisfaction. Mathematical Problems in Engineering, 2021(5), 1-17.

[18] Shi, Y., & Peng, Q. (2021). Enhanced customer requirement classification for product design using big data and improved kano model. Advanced Engineering Informatics, 49(1), 101340.

[19] Ho, W., & Ma, X. (2018). The state-of-the-art integrations and applications of the analytic hierarchy process. European Journal of Operational Research, S037722171730797X.

About the Author

Ying Dai, 1986.10, Female, Han Chinese, Leping, Jiangxi province, Ph.D., Lecturer, Industrial design, cultural and creative design, Lishui University.

Shusen Zhang, 1985.4, Male, Han nationality, Linyi, Shandong Province, Ph.D. candidate, lecturer, mechanical design, underwater engineering, Lishui University.