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Article

Combining AIGC and Virtual Simulation Technology to Enhance Personalization of Jewelry Design

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Abstract: Empowered by emerging technologies such as 5G, big data, cloud computing, artificial intelligence is developing rapidly, and its application has received widespread attention from various industries. Empowering design, such as jewelry design, through AIGC can improve efficiency, expand creativity, and promote the innovative development of the jewelry design profession. The study firstly imports the data into 3DMax software to complete the construction of the jewelry 3D model, and in the process of model construction, Photoshop and Lidar point cloud computing are used to control the model's color matching and height distance. Based on the genetic algorithm, an interactive genetic algorithm based on user preference model is proposed. After adding the group preference information, the preference dominance relationship of the current user changes only slightly, indicating that this algorithm still focuses on user preference, which is conducive to the rapid tracking of user preference when it changes. Through the method of user research, the KANO model is used to grade the attributes of functional requirements, and design innovations are proposed.

Keywords: genetic algorithm; user preference; jewelry design; three-dimensional design; KANO model

1. Introduction

In the information age, advancements in image recognition technology and human-computer interaction technology have transformed how people observe, perceive, and experience physical objects. As a result, there is a growing demand for enhanced experiential quality throughout the entire process of jewelry design and display. Traditionally, the jewelry industry has relied on physical objects, images, and videos for design and display purposes; however, these methods often result in suboptimal design outcomes, display effects, and wearing experiences [1-2]. Virtual reality technology can enhance visual imagery effects. When applied to the jewelry industry, designers can use virtual objects to express design concepts during jewelry design; during jewelry display, the virtual objects serve as a reflection of real jewelry and can also showcase the material properties of real jewelry. Although these are virtual objects, they can give consumers a sense of "reality," providing them with a new visual experience and introducing a new form of presentation to the jewelry industry [3-5].

As AIGC continues to evolve, creative art design is undergoing transformation, facing unprecedented opportunities and challenges. Especially with the emergence of tools like ChatGPT, Midjourney, and Stable Diffusion, the barriers to artistic creation are gradually lowering, with more users beginning to experiment with AI technology to create art based on their aesthetic preferences. Art design empowered by AI technology possesses unique creativity and expressive forms, not only redefining the boundaries of content creation but also breaking through the limitations of traditional art [6-8].

Against the backdrop of the continuous development of AIGC technology, the pace of change and development in the jewelry design industry has accelerated. Through AIGC, jewelry designers can use artificial intelligence creation and experimentation platforms to quickly understand consumer preferences and market trends, respond promptly to market demands, provide data support for design practices, and enhance the accuracy and market acceptance of designs [9-10]. Secondly, under the creative guidance of jewelry designers, AIGC can analyze design databases through deep learning and machine learning, identify and extract design elements based on popular trends, and provide references for jewelry designers; it can automatically generate design sketches and proposals to accelerate the design process and improve efficiency; it can generate a large number of design variations, offering jewelry designers more diverse and abundant options, thereby increasing the flexibility and innovation of jewelry design [11-12]. Thirdly, through deep learning, AIGC can achieve personalized customization, enhance user experience, and meet market demands [13]. Finally, AIGC promotes interdisciplinary collaboration, such as integrating knowledge from psychology, sociology, and other disciplines to provide diverse perspectives for jewelry design [14].

Modern jewelry personalized design still has shortcomings in many aspects. To address issues such as insufficient innovation in jewelry design, literature [15] applies 3D printing digital technology to jewelry design, utilizing it to obtain the two-dimensional slice images required for jewelry design, creating more personalized and unique jewelry works, and conducting related experiments to validate its high application value. To address the issue of limited design elements in jewelry, literature [16] employs AI-based 3D technology, utilizing the ComfyUI AI tool, to integrate collected traditional Chinese elements, converting 2D designs into 3D models, and further refining them through manual optimization to dynamically showcase the essence of traditional Chinese culture. To address the issue of irregular shapes in jewelry design, Literature [17] applied computer-aided technology to jewelry art design. It studied an interpolation algorithm based on triangular BB faces, enabling faster processing of spatial data point triangulation, and more precise and rapid completion of three-dimensional modeling of jewelry, thereby effectively enhancing the effectiveness of jewelry art design.

Additionally, Literature [18] combines computer vision technology with jewelry design, establishing corresponding algorithmic rules and parameters to intelligently generate jewelry designs through computation. This approach breaks through the limitations of traditional jewelry creation, offering new possibilities for realizing complex jewelry structures, while significantly improving the efficiency of process design. Literature [19] employs an optimized ecological design method to develop an artificial neural network (ANN) model, establishing a quantitative relationship between design attributes and sustainability indicators, and conducts research on the optimization of eco-friendly jewelry design. Literature [20] suggests that recommendation algorithms can help jewelry designers better understand user needs, and conducts a feasibility analysis and discussion on the application of recommendation algorithms in jewelry art design, aiming to provide jewelry designers with personalized jewelry customization capabilities to better meet consumer demands.

3DMax software is used for three-dimensional jewelry design operation, and the genetic algorithm is combined with 3DMax to complete the jewelry design, which improves the precision of the design results, and can ensure the artistry and integrity of the jewelry design results. Then an adaptive value estimation method in line with the user's emotional preference is given - interactive genetic algorithm based on the user preference model, taking the jewelry design book as a case study, using similar groups of user information and combining with the proposed algorithm for algorithmic analysis. For the user demand research of jewelry design, attribute division of functional demand points according to the KANO model is carried out to realize jewelry personalization.

2. Personalized Jewelry Customization Based on Interactive Genetic Algorithm

2.1. 3D Modeling of Jewelry Based on AIGC and Virtual Simulation Technology

2.1.1. Sketching Jewelry

According to the understanding of the previous three-dimensional jewelry design method, the sketch of jewelry is usually completed in the form of hand-drawing. Based on the requirements of three-dimensional jewelry design, CG digital drawing technology is used to complete the design of jewelry sketches. The initial sketch of the jewelry is recorded into the computer through the use of digital drawing, and the sketch is completed by using the multi-touch digital board. The sketches are two-dimensional and saved in DWC format, which can transfer the jewelry image data directly to 3DMax software. In the process of sketching, focus on the positional details of the three parts of the points, lines and surfaces to ensure that they provide the basis for the construction of the next three-dimensional model. In jewelry design, the focus of point elements mainly refers to the key points of the jewelry, the vertex, and the key points of the original stone. There is a difference between each point, thus in the drawing process, its position is realized precisely set to ensure the accuracy of the source of the design drawing. There are also a lot of line elements in the sketch, according to the position of the points, to obtain the jewelry line elements. Finally, through the above elements to form the jewelry surface elements. The three-dimensional design model of jewelry is realized by stretching, trimming and extruding the sketch. Thus, strict control of these three elements is the key in jewelry design.

2.1.2. Establishment of a Three-Dimensional Model of Jewelry

The sketches after drawing are used to construct a 3D model of the jewelry. The processed sketch base map is imported into 3DMax software, and since it is a two-dimensional image, the height of the jewelry should be accurately controlled in the process of modeling. Use Lidar point cloud data to complete the estimation of the height of the finished jewelry design. The texture produced should be consistent with the characteristics of the jewelry, so as to ensure the authenticity of the design. In order to ensure the orderliness of the three-dimensional model construction, the modeling process is designed, and the specific content is shown in Figure 1.

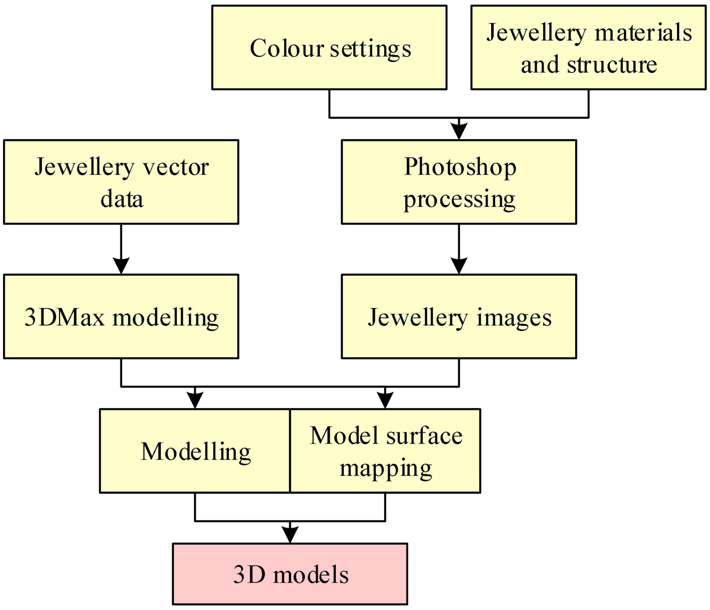

Figure 1. 3D model build process.

2.1.3. 3D Model Detail Optimization

Electronic painting technology and 3DMax software are used to complete the basic three-dimensional model design of jewelry, and in order to achieve the consistency between the jewelry design model and the sketch, the evolution theory in the genetic algorithm is used to optimize the accuracy of its model.

Setting axt, ayt, azt corresponds to the error values of X, Y, Z axes of the 3D model respectively, there are:

$$\begin{cases} axt = \sqrt{a^2 x_{st} + a_s^2 \sin\theta + a_z^2 \cos^2\theta} \\ ayt = \sqrt{a^2 y_{st} + a_s^2 \cos\theta + a_z^2 \sin^2\theta} \\ azt = \pm\sqrt{a^2 z_{st} + a^2 z} \end{cases} \tag{1}$$

where: ax, ay, az is the resolution error of X, Y, Z axes; $a^2 x_{st}, a^2 y_{st}, a^2 z_{st}$ is the photographic center error of X, Y, Z axes; and θ is the angle of image rotation. The model error can be derived using equation (1), and the genetic algorithm is used to correct the model error.

Setting Δ as the absolute error of the 3D model, c as the relative error, a as the calculated value, and b as the sketched value, there is the following equation:

$$\begin{cases} \Delta = a - b \\ c = \Delta / (a + b) \end{cases} \tag{2}$$

The relative error in the model is reduced by this formula to ensure that the length and width of the 3D model are consistent with the sketch data. Setting the true error of the model as e, the elevation of the model as H_A, the elevation of the sketch design as H_B, the error of the measured value as n, and the number of calculations as m, we have:

$$\begin{cases} e = H_A - H_B \\ F = \dfrac{m}{\sqrt{n}} = \pm\sqrt{\dfrac{[e]}{n(n-1)}} \end{cases} \tag{3}$$

Error optimization of the model's elevation through the above process, combined with equation (2) to complete the whole process of error optimization of the model data. Authenticity should be ensured in terms of texture. Under the premise of clear texture, the amount of data should be as small as possible. PS is used to deform the texture, and the brightness and color tone are adjusted according to different light. At this point, the jewelry three-dimensional design method is completed.

2.2. User Preference Model

2.2.1. Scope of Application

The initial idea for modeling user preferences in this paper comes from the cognitive laws of users in the interactive solution process of implicit goal decision problems. The decision objective of the implicit objective decision problem is difficult to be expressed in a structured way, which leads to the need to use manual evaluation to give adaptation values for evolved individuals. For the same optimization objective, there are obvious differences in the preferences of different users, which are caused by the differences in their knowledge background, cultural tendencies and aesthetic interests. Even for the same user, his/her preference is not static, but gradually becomes clearer from ambiguity and more stable from fluctuation with the progress of IGA interaction and evolution process.

2.2.2. Generation and Timing of Use

There is drift in user preference in IGA, and user preference is not only related to the evolved individuals, but also related to the evolutionary time, i.e., for the same evolved individual, the preference value may be different in different evolutionary generations. This phenomenon is not difficult to understand, people's evaluation of things is often a process from fuzzy gradually clear, in the initial stage of evolution, the user is not familiar with the evaluation object, the preference is fuzzy; with the advancement of the evolutionary process, the user in the process of constantly adjusting their own preferences gradually familiar with the evaluation object, the preference is also gradually clear. At the same time, as the evaluation process advances, the algorithm tends to converge will lead to the emergence of more similar individuals or individual components, for the user, too many evaluations and assigning values to individuals with small differences will bring a great physiological and psychological burden, which is often referred to as the user fatigue problem. Therefore, it is worthwhile to study the generation and timing of the user preference model to solve the user fatigue problem.

2.2.3. User Preference Modeling

User preference is defined as people's rational choice of goods or services, which is the comprehensive result of the user's cognitive and psychological feelings weighing. And the user preference model is to digitize the user preference and complete the nonlinear mapping from human subjective psychological space to objective feature space. The user preference model in this paper is built on the basis of each independent component. We define the user preference model M as a binary form, notated as $M = (I, F)$. where I is a matrix with each row representing genotype information of an evolved individual in the population, and F is a column vector representing the adaptation values of the evolved individuals in the corresponding I. The specific representation of M is as follows:

$$M = \begin{pmatrix} a_{11} & \cdots & a_{1m} \\ \vdots & \ddots & \vdots \\ a_{n1} & \cdots & a_{nm} \end{pmatrix} \begin{pmatrix} f_1 \\ \vdots \\ f_n \end{pmatrix} \tag{4}$$

where a_{ij} represents a local gene segment that can and only can express a certain functional significance, i.e., the gene code corresponding to a certain partial phenotype of the evolved individual, and f_i

represents the fitness value of the evolved individual $\left(a_{i1}\ a_{i2}\ \cdots a_{im}\right)$. Where n represents the number of evolved individuals in the user preference model, m represents the number of components of evolved individuals, $i = 1, 2, \cdots, n$, $j = 1, 2, \cdots, m$.

2.3. Interactive Genetic Algorithm Foundations

2.3.1. Genetic Algorithms

The basic idea of genetic algorithm comes from Darwin's theory of evolution and Mendel's genetics. The principle of evolution in the theory of evolution is "the survival of the fittest", i.e., in the process of competition between individuals, only those individuals who have adapted to the environment can be retained, and with the continuous advancement of the evolutionary process of the population, the advantageous genes of the advantageous individuals will be inherited by the next generation, and the genes in the process of evolution will undergo selection, crossover and mutation. Mutation, so that the new generation of individual genes on the basis of retaining the advantageous genes of the previous generation, to ensure genetic diversity, thus ensuring the diversity of the population, that is to say, the new generation of individuals better adapted to the survival of the competitive environment. Genetic algorithm is to emulate this biological evolutionary process, in the evolutionary process, constantly eliminating the inferior gene individuals, will solve the problem of approximate optimal solution to the optimal solution is constantly approaching [21]. The main concepts in genetic algorithm are as follows:

(1) Individual: corresponding to the concept of chromosome in genetics, each individual contains multiple gene segments, and each gene segment has a specific expression type.

(2) Population: a collection of multiple individuals constitutes a population.

(3) Gene: a segment contained in an individual that characterizes the individual. In binary coding, consisting of multiple 0s and 1s, each gene segment (a string of 0s and 1s) has a specific expression.

(4) Adaptive value: the ability of an individual to survive in the current environment. The larger the adaptive value, the greater the chance of the individual's ability to survive or participate in evolution, and the smaller the adaptive value, the greater the chance that the individual will be eliminated in the process of evolution.

(5) Selection: that is, the "survival of the fittest" in genetics, the process of screening individuals to participate in evolution.

(6) Crossover: corresponds to the concept of hybridization in genetics, i.e., an operation in which genes are exchanged between individuals.

(7) Mutation: called mutation in genetics, i.e., the process of localized genetic change in an individual due to environmental and other factors.

2.3.2. Interactive Genetic Algorithms

The theoretical basis of interactive genetic algorithm comes from genetic algorithm, and during the operation of genetic algorithm, an explicit fitness function must be specified to automatically calculate the fitness value of the evolved individual, which limits the application of genetic algorithm in optimization problems with unclear objective function. Interactive genetic algorithm can effectively solve the implicit objective optimization problem by evaluating the adaptation value of the evolved individual through human subjective evaluation instead of the algorithm, and combining with the global search and optimization ability of the genetic algorithm.

The basic principle of interactive genetic algorithm is as follows: firstly, the algorithm randomly initializes a population and presents the performance of all individuals in the population to the user; then, the user assigns the adaptation value to the evolved individual according to his/her personal feelings through the comparison between different individuals and between the current individual and the ideal individual in his/her mind, and the human and the algorithm work together to complete the process of the population evolution; finally, the user's satisfied individual is searched for the best fitness value in the feasible domain of the problem to be optimized. Finally, the user-satisfied individual is searched in the feasible domain of the problem to be optimized [22].

The flowchart of interactive genetic algorithm is shown in Fig. 2, compared with genetic algorithm, interactive genetic algorithm can be divided into two parts: the first part is human-computer interaction, the user evaluates the adaptation value of the evolved individuals, and the evaluation method is generally that the user assigns the corresponding adaptation value to all the individuals in the population, or it can also only rate the most satisfied individuals in the population; the second part is genetic evolution, through genetic operations (selection, crossover and mutation) to obtain a new generation of the population, which is then evaluated by the user. The interactive genetic algorithm is a process of repeating the above process to find a user-satisfied solution among all feasible solutions.

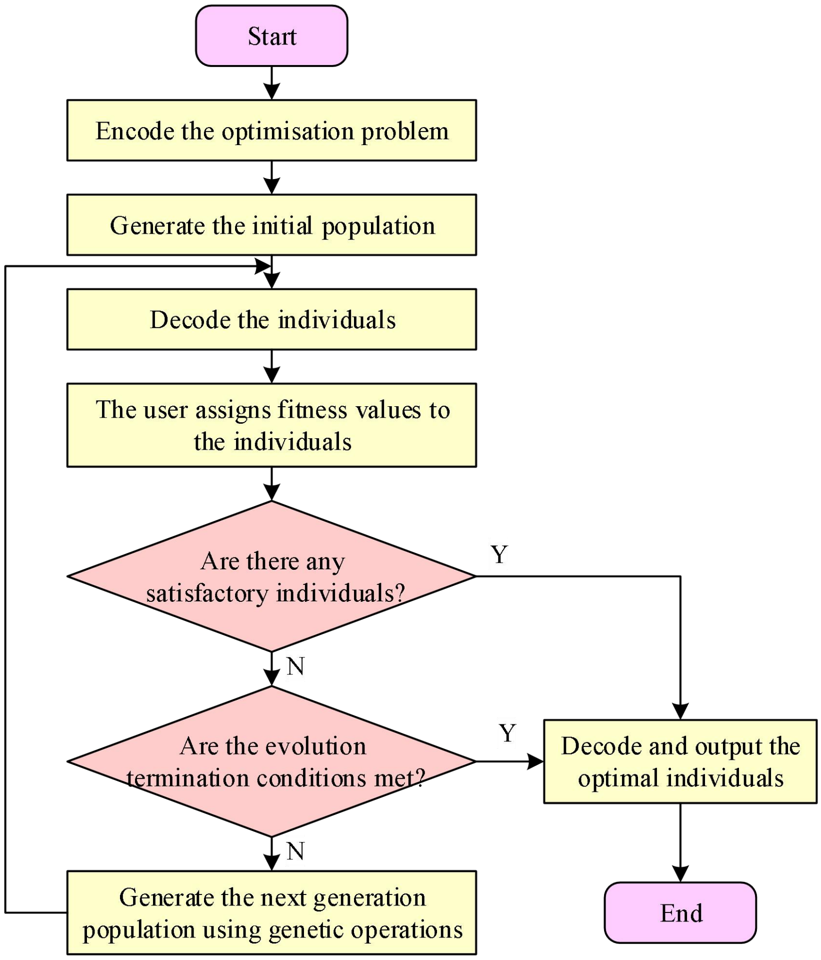

Figure 2. Interactive genetic algorithm flowchart.

The IGA algorithm has the following characteristics in addition to those of the GA algorithm:

(1) Small population size and few evolutionary generations

The running process of the interactive genetic algorithm is completed by both human and machine, and every time a new population is generated, human beings have to participate in the evaluation of the adaptation value of the new generation of evolved individuals, and frequent human-machine interaction can easily lead to user fatigue, which in turn affects the accuracy of the user's evaluation of the adaptation value of the evolved individuals. Therefore, the setting of the population size should not be too large, and the number of evolutionary generations should be as small as possible.

(2) Subjectivity of user evaluation of individuals

In the process of IGA operation, the adaptation value of the evolved individual is directly given by a person, and each person's preference as well as his/her understanding of the problem varies, and the results of evaluation of the same individual by different people vary greatly. In addition, even the same person may fluctuate the evaluation value of the same individual at different times and in different environments. This is the subjectivity that IGA carries in the calculation of adaptation values of evolved individuals.

(3) Bias in user evaluation of individuals

The user's evaluation of the adaptation value of the evolved individual is inaccurate or biased by the influence of itself and the external environment during the execution of the algorithm. There are two main reasons: first, in the pre-evolutionary period, the user's cognition of the evaluation object is not clear, often the more complex the evaluation problem, the more fuzzy the clarity of this cognition, with the deepening of the evolutionary process, the user's cognition will be more and more clear, and at this time, the user's adaptive value of the evolved individual scoring can be more in line with the actual situation; second, with the user involved in the interaction time, the user is gradually fatigued, and in the fatigue state users are often difficult to give accurate adaptation value scores.

(4) Uniqueness of optimization results

As mentioned earlier, user evaluation is subjective and different people have different preferences, which can lead to different results in problem solving. In addition, users may have multiple preferences, i.e., they are satisfied with multiple feasible solutions in the feasible domain of the optimization problem.

2.4. Interactive Genetic Algorithm Based on User Preference Modeling

2.4.1. Chromosome Coding

In the operation of the genetic algorithm, how to realize the feasible solution of the problem from the solution space to the search space that the algorithm can deal with the conversion is the key to guide the subsequent genetic operations of selection, crossover, and mutation, and the method of this conversion is known as coding. Currently the most commonly used and simple to implement is the binary coding method.

2.4.2. Estimation of Adaptation Values

In genetic algorithms, the adaptation value is used to measure the degree of excellence of the evolved individuals in the population that helps to find the most satisfactory solution in the optimization process, and individuals with high adaptation values have a higher probability of being inherited to the next generation. In IGA, the user participates in the interaction to directly give the adaptation value to the evolved individuals, i.e., the adaptation value of the evolved individuals represents the degree of user preference, but considering the problem of human fatigue, if we want to find the most satisfactory solution as quickly as possible in a large solution space, we need to consider the evaluation by the computer based on the obtained preference model instead of the user.

In order to reflect the user preference, this paper establishes the user preference model of the historical evaluation information selected in the user has evaluated individuals in the adaptation value higher than the average value of the individual information, in order to facilitate the narrative, we will be evaluated by the user has evolved individuals in the adaptation value higher than the average value of the individual known as the more preferred individuals, the following user preference modeling process mentioned in the history of the evaluation information come from the user's more preferred individuals set. Combining the above concepts, the formula for the constituent preference value $f(a_{ij})$ is as follows:

$$f(a_{ij}) = \sum_{i=1}^{k} \frac{f_i w_j}{l} = \frac{1}{l} \sum_{i=1}^{k} f_i w_j \tag{5}$$

where l represents the total number of more favored individuals that have been evaluated by the user, k represents the number of more favored individuals that have been evaluated by the user that contain a_{ij}, f_i denotes the value of the adaptation of the more favored individuals that have been evaluated by the user that contain a_{ij}, and w_j refers to the weight of the component corresponding to a_{ij}, where $\sum_{j=1}^{m} w_j = 1$.

Considering the problem of correlation among the constituent parts of evolved individuals, this paper gives the definition of preference combination. In the process of evolution, when the frequency of occurrence of fixed component combinations exceeds a certain threshold value α, such component combinations are called preference combinations. In the adaptation value estimation stage, the adaptation value of the evolved individual containing the preference combination should be increased accordingly, and a preference combination coefficient λ needs to be introduced here, which is related to the number of times the combination occurs $Freq(Comb)$, and λ is also closely related to the number of constituent parts in the combination $Count(Comb)$, i.e., the higher the frequency of occurrence of the preference combination, and the more constituent parts are included in the preference combination, the larger the value of λ. Among them, $Freq(Comb) = 1, 2, \cdots, l$, $Count(Comb) = 2, 3, \cdots, m-1$.

$$\lambda = \frac{Freq(Comb)}{l} \times \frac{Count(Comb)}{m} \tag{6}$$

Let x represent any newly evolved individual in the IGA, α_c denotes the specific threshold value selected, and the estimated adaptation value of evolved individual x is given in the following equation by combining the adaptation values of each component and taking into account the influence of the association between the components:

$$f(x)=\begin{cases}(1+\lambda)\sum_{j=1}^{m} f(a_{ij}) & \alpha \geq \alpha_c \\ \sum_{j=1}^{m} f(a_{ij}) & \alpha < \alpha_c\end{cases} \tag{7}$$

In summary, the user preference model in this paper is based on the adaptation values of each independent component. In order to protect the advantageous genes from being destroyed, the individual with the largest adaptation value in each generation will be directly retained to the next generation.

2.4.3. Algorithm Flow

The basic idea of the UPM-IGA algorithm is as follows: firstly, a simple IGA operation is performed, and the user assigns an adaptation value to each generation of evolved individuals by scoring; once the user feels fatigue, machine learning is performed based on the existing information of the genes and adaptation values of the more preferred individuals, so as to construct a user preference model, and the adaptation values of the newly generated individuals in the subsequent evolutionary process are automatically estimated, so that machines can replace manual labor, and thus reduce the number of user scoring times and reduce user fatigue. The number of user ratings is reduced and user fatigue is reduced.

The steps of the algorithm are described below, and the flow is shown in Figure 3.

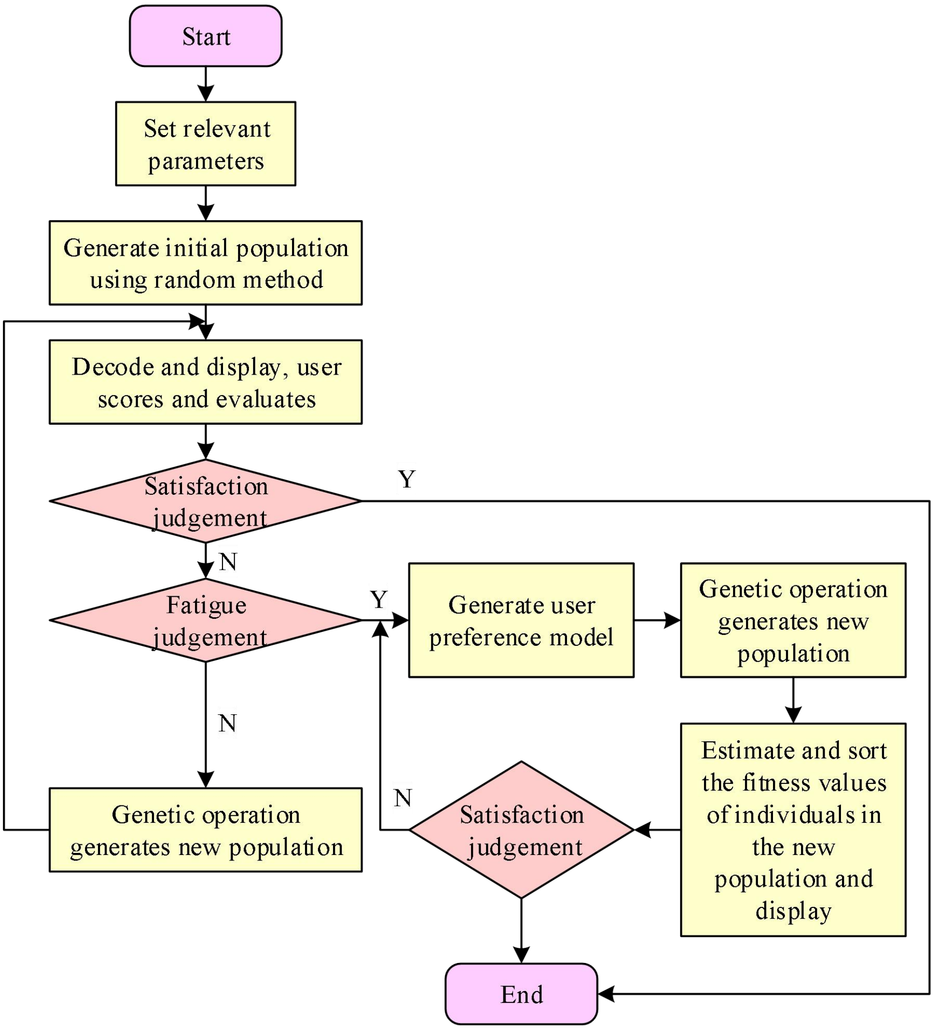

Figure 3. Interactive genetic algorithm process based on user preference model.

3. Personalization Effects of Jewelry Design

3.1. Experimental Setup

3.1.1. Experimental Background

This experiment is a simulation experiment based on the classification of jewelry design books. There are 234 jewelry design books, with 522 group users, containing 2978 group user information.

In order to fully illustrate the reasonableness as well as the effectiveness of the proposed algorithm, this experiment consists of two parts, the first part is to verify the reasonableness of incorporating the group user information and the effectiveness of the possibility-conditional preference network constructed by incorporating the group preference information, and the second group is to illustrate the overall performance of the proposed algorithm by comparing the two different comparison experiments.

3.1.2. Parameter Setting

The individual books need to be coded when performing genetic operator operations. This chapter still uses binary to encode the books according to the book attribute block. This experiment jewelry design books are divided into 7 books as shown in Table 1, there are a number of values taken under each category of attributes, a total of 28 in this experiment, which requires 20 bits of binary code. In the experiment, the three types of comparison algorithms are used roulette selection, single-point crossover and mutation, and crossover and mutation probability of 0.6, 0.1. and the population size is 8, according to people's browsing habits, in the screen to display the goods should not be too much, too much will be prone to user fatigue, should not be too little, too little will increase the frequency of the user's search, but also easy to produce user fatigue.

Table 1. Attributes' coding.

Book	Coding
Jewels and gemstones	A1
A history of jewellery	A2
Jewelry design	A3
Product drawing and technique	A4
Treasure and legend	A5
A thousand lights are shining	A6
Timeless jewels in the museum	A7

3.2. Factor Analysis

Factor analysis is a technique for downscaling and simplifying data. It represents the underlying data structure by examining the internal dependencies between variables using a handful of variables, these abstract variables are called factors and respond to the vast majority of information about the data.

After the first round of scoring by the user, the adaptation values for each individual are derived and the coded and adapted values for each factor are put into SPSS for analysis.

The results of genetic recombination variation were entered into SPSS for analysis and the results were obtained as shown in Table 2. From the correlation matrix of the table, it can be visualized that the correlation between the factors is large, and KMO and Bartlett's experiments were performed before factor analysis.

Table 2. Correlation matrix.

Head		Chain	Buckle	
Correlation	Head	1.008	0.762	0.694
	Chain	0.762	1.008	0.579
	Buckle	0.694	0.579	1.008

The KMO value is between 0 and 1, which is used to check the correlation between the variables; the closer the KMO value is to 0, the weaker the correlation between the variables, which is not suitable for factor analysis; the closer the KMO value is to 1, the stronger the correlation between the variables, and the more desirable the effect of factor analysis is. In the actual analysis, the effect is more ideal when the KMO value is above 0.7. Bartlett's spherical test is used to determine the correlation between the variables and whether each variable is independent. The test value is shown in Table 3, by SPSS test results show that Sig (i.e., significance) is less than 0.05, indicating that there is a correlation between the variables, and the factor analysis is effective. Combining the two indicators in the table, it can be learned that in this case, the KMO value is 0.684, which is close to 0.7, and the significance of Bartlett's experiment is 0.001, which is less than 0.05, which indicates that there is a correlation between the variables, and factor analysis can be performed.

Table 3. KMO and Bartletts experiment.

KMO sampling availability number	0.684	
Bartlett sphericity test	Approximate card	26.017
	Freedom	2
	Significance	0.001

The common factor variance and variance explanation are shown in Table 4 and Table 5. In Table 4, the eigenvalue of component 1 is greater than 1, which can explain 79.343% of the variance, and the effect is more satisfactory, so component 1 is extracted as the main component and other factors are discarded.

Table 4. Common factor variance.

	Initial	Extraction
Head	1.000	0.863
Chain	1.000	0.758
Buckle	1.000	0.713

Table 5 Total variance interpretation

Constituent	Initial eigenvalue		
	Total	Percentage of variance	Cumulation %
1	2.472	82.4	79.343
2	0.433	14.43	93.752
3	0.095	3.17	100.00

According to the above content to draw the gravel map is shown in Figure 4, through the gravel map that the user is more sensitive to HEAD.

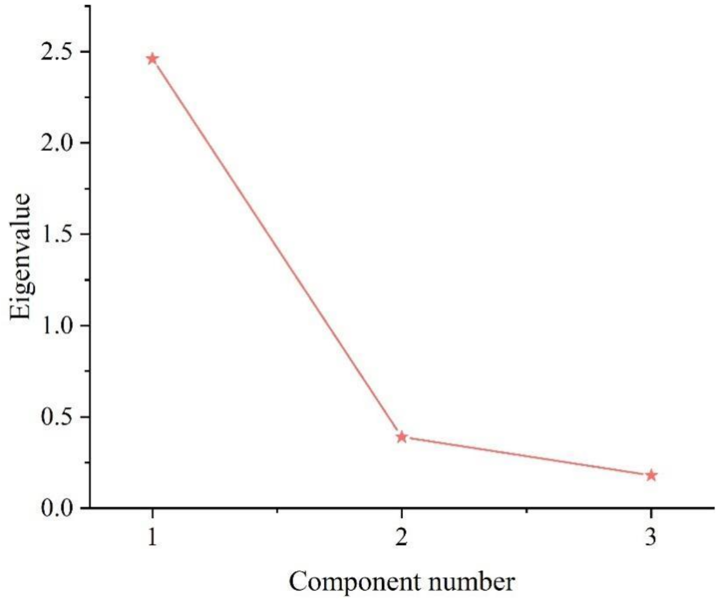

Figure 4. Rubble map.

3.3. Experimental Results and Analysis

In order to illustrate the overall performance of the algorithm, two groups of comparative experiments are done. The first group of comparative experiments is to search for books on the history of jewelry design as an example, and the algorithm proposed in this paper, UPM-IGA, is compared with the algorithm, IGA-PCP, in order to illustrate the impact of adding similar groups of user information. The second set of comparison experiments is to search for books on “product hand-drawing techniques”, the algorithm in this paper is compared with IGA-BP and traditional genetic algorithms to illustrate the overall performance of the algorithm in this paper.

(1) Reasonableness and feasibility of adding group users

Incorporate group user information into the current user preference network, here to verify whether the method is reasonable. Taking one experiment as an example, the current user preference attribute weights are shown in Fig. 5, and the preference of attribute values are shown in Fig. 6. The comparison before and after adding group preference information is shown in Fig. 7 and Fig. 8. Here t=0.55, k=0.6. From Fig. 5-Fig. 8, it can be seen that after adding group preference information, the preference dominance relationship of the current user changes only slightly, indicating that this algorithm is still dominated by the current user's preference.

From Figure 8, it can be seen that there is new attribute value preference information in the similar group, which is not involved in the current user preference information, then incorporating the new attribute value preference into the current user preference information can effectively explore the user's potential preference, and it can improve the diversity of the algorithm, and it is also conducive to the rapid tracking of user preference when the user's preference is changed, and accelerate the algorithm's convergence speed.

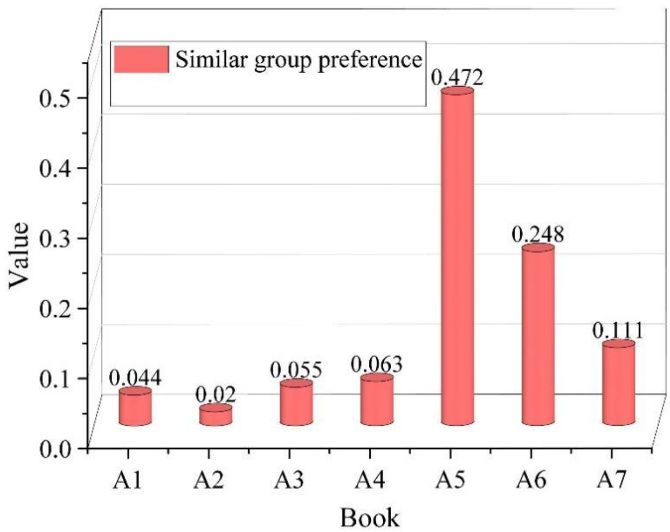

Figure 5. The attributes’ preference weight of similar group.

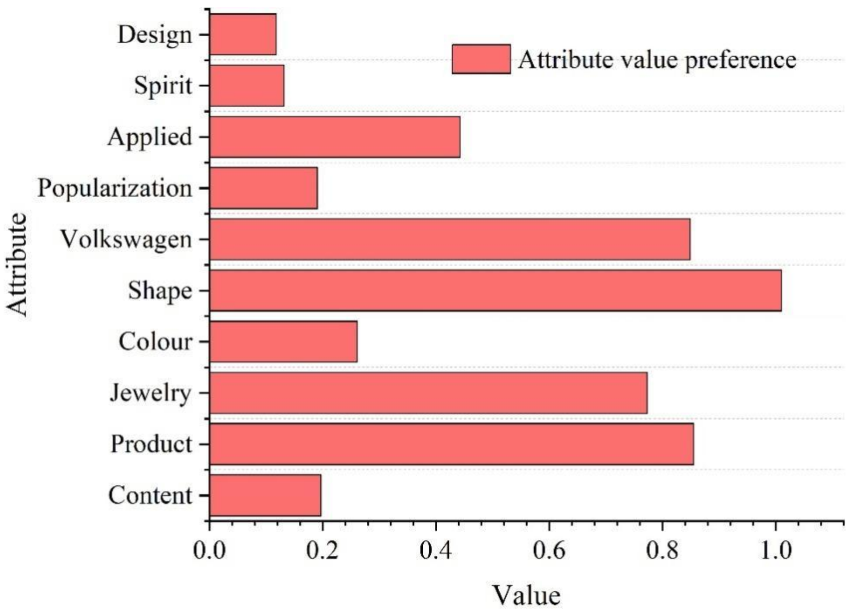

Figure 6. The attributes’ preference degree of similar group.

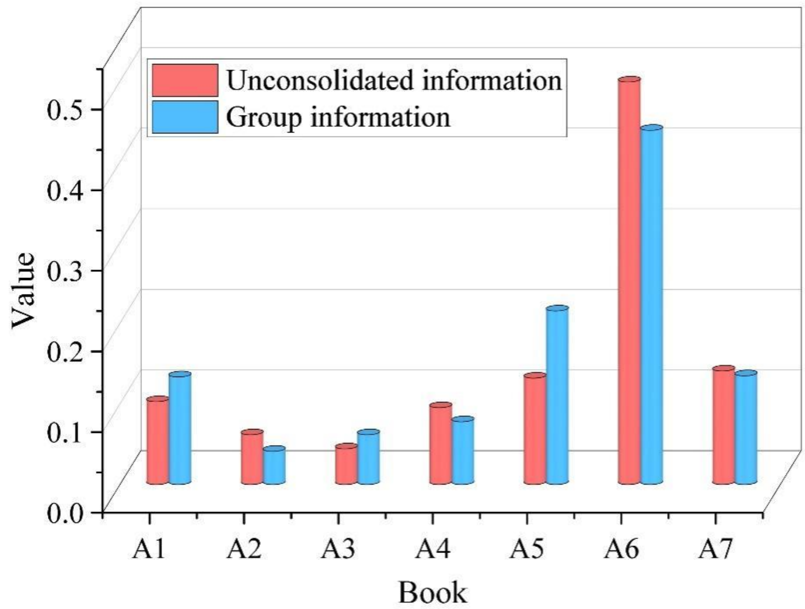

Figure 7. The preference weight relation of attributes.

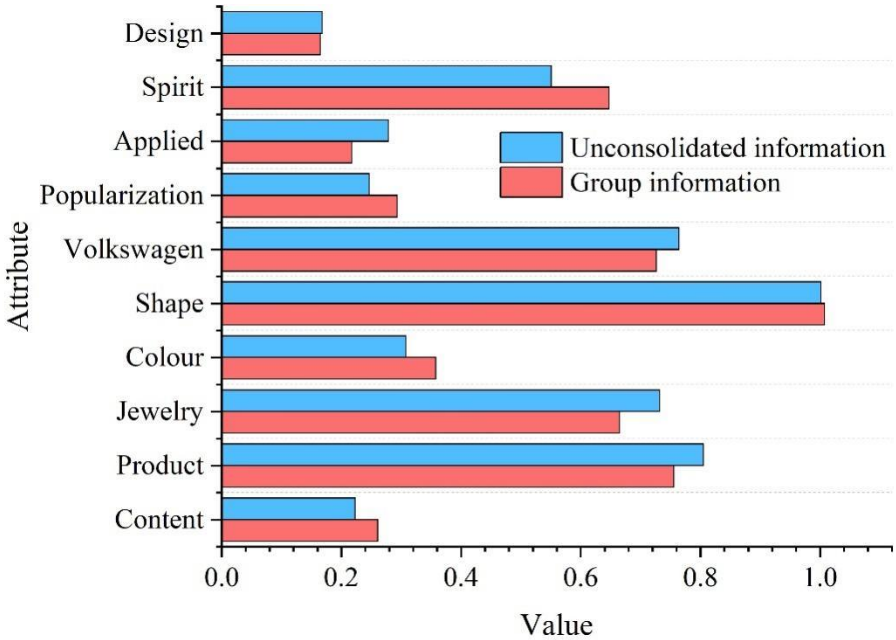

Figure 8. The preference degree relation of values.

Taking one experiment as an example, the adaptation values of individuals in each generation are recorded and averaged, and the changes in adaptation values are shown in Table 6. It can be seen that whether it is UPM-IGA or IGA-PCP algorithm, the adaptation value increases gradually, which indicates that both algorithms can effectively track user preferences; on the other hand, the average adaptation value of individuals in IGA-PCP algorithm is obviously smaller than the average adaptation value of individuals in UPM-IGA algorithm, which indicates that the individuals are more in line with the user preference needs after adding group information.

Table 6. The average fitness.

Evolutionary algebra	UPM-IGA	IGA-PCP
1	86.93	34.27
2	107.41	60.12
3	130.31	74.71
4	136.65	95.7
5	155.2	120.58

(2) Comparison Experiments

To illustrate the overall performance of the algorithms, Algorithm UPM-IGA is compared with Algorithm IGA-PCP, Algorithm IGA-CP, and Algorithm IGA in a comparison experiment. The number of evolutionary generations, the search time, the number of direct user operations, and the ratio of heterogeneous individuals are recorded, and the results are shown in Table 7. From the experimental results, it can be seen that Algorithm UPM-IGA can accelerate the convergence speed of the algorithm, improve the efficiency of the algorithm, and reduce the user fatigue.

Table 7. Experimental results.

Algorithm	Mean evolutionary algebra	Average search time (s)	User interaction number	Heteroscale
IGA	13	185.32	18.214	0.642
IGA-CP	11.54	129.275	14.729	0.631
IGA-PCP	6.79	122.649	9.147	0.709
UPM-IGA	5.82	99.793	7.422	0.885

3.4. Jewelry Design Needs Analysis

KANO model two-dimensional quality model, invented by Noriaki Kano and others, a professor at Tokyo Institute of Technology, Japan, for the classification and ranking of user needs and tools [23], through the analysis of the impact of user needs on user satisfaction, reflecting the nonlinear relationship between the functional characteristics of the product and the degree of user satisfaction, as shown in Fig. 9, the horizontal axis indicates the degree of the product's functional characteristics to have, the more to the right, the higher the degree of having. the higher the degree, the vertical coordinate axis indicates the user's satisfaction with the functional characteristics of the product, and the more upward indicates the higher the degree of user satisfaction.

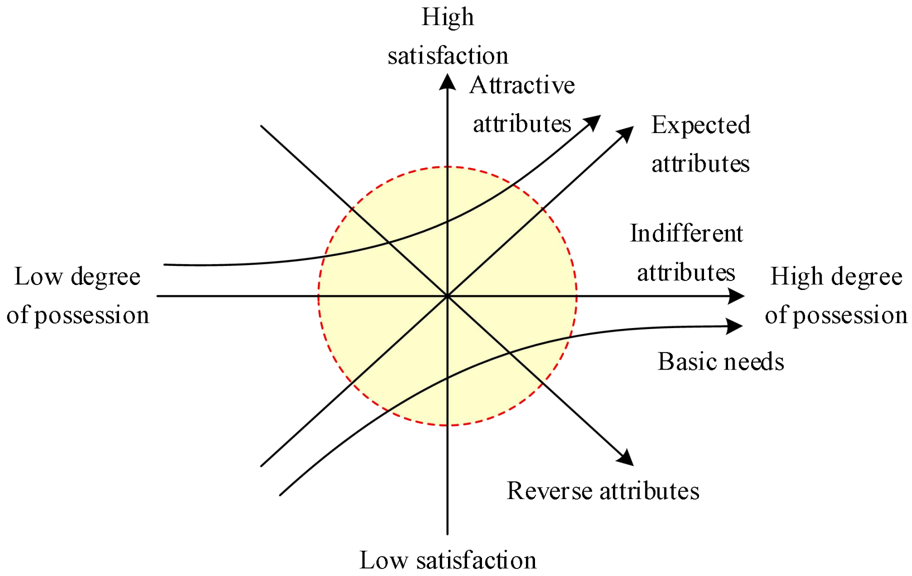

Figure 9. KANO model.

3.4.1. KANO Model Questionnaire Research

Combined with competitor analysis and user interviews, to determine the user functional requirements of the pearl display applet, through further collation and analysis of functional requirements, put forward 22 functional requirements of the pearl shopping applet platform: Function 1: According to the user's needs, the platform to provide 1 to 1 customization services; Function 2: According to the trend, the platform can recommend the popular styles of jewelry; Function 3: The platform has a real mannequin styles to wear Pictures or videos; Function 4: the platform provides products how to maintain the pearl jewelry recommendations; Function 5: According to the user's personal preferences, independent choice of accessories pearl with; Function 6: According to the trend of providing styles with reference to the product map; Function 7: According to the products generated by the individual DIY, the platform to provide the order of production services; Function 8: According to the products generated by the individual DIY, the platform to open WeChat, QQ, Microblogging and other platforms to share the function; Function 9: shopping operation is smooth and simple, the elderly are also easy to operate; Function 10: the interface display style is simple; Function 11: the user can choose whether the platform information pop-up window to accept the activity reminders; Function 12: the establishment of the platform community, and we can share; Function 13: jewelry online design to provide customized price estimate interval; Function 14: the platform provides users with jewelry design Auction and competition channel; Function 15: Customer service channel is obvious and easy to find; Function 16: Selling products class level classification is clear, the price range is clear; Function 17: The platform provides jewelry 3D model display; Function 18: Recommended for users to recommend jewelry clothing with recommendations; Function 19: Users can upload their own design, the business can be purchased into the production; Function 20: According to the user's needs to customize the color of the page Function 21: Provide jewelry appraisal service window; Function 22: Product classification is clear, you can quickly find products according to demand.

The research adopts both online and offline research methods, 117 questionnaires were collected through online questionnaire star, and 31 paper questionnaires were collected offline. 8% were under 25 years old, 60% were 25-35 years old, 19% were 35-40 years old, and 13% were over 40 years old.

The results of the online and offline questionnaires were collated, and the functional requirements were classified and counted according to the Kano model classification table, as shown in Table 8, and the user's needs were divided into five levels, with "O" representing the desired attribute. "M" stands for basic attribute; "A" stands for charismatic attribute; "R" stands for inverse attribute; "I" stands for indifference attribute; Among them, "Q" represents contradictory answers, which can be ruled out. Draw the table of functional requirements attributes, as shown in Table 9.

Table 8. KANO Requirement classification comparison table.

Users and requirements		Reverse problem				
		Surprise	Of course	It doesn't	Grudging	Dislike
Forward problem	Surprise	Q	A	A	A	O
	Of course	R	I	I	I	M
	It doesn't	R	I	I	I	M
	Grudging	R	I	I	I	M
	Dislike	R	R	R	R	Q

Table 9. Classification of functional requirements for jewelry design.

Functional requirement	A	O	M	I	R
1	89	1	5	35	0
2	35	2	19	73	1
3	30	11	31	55	3
4	31	8	35	52	4
5	54	6	22	43	5
6	45	11	17	52	5
7	74	3	8	38	7
8	45	3	8	67	7
9	56	14	10	45	5
10	31	17	20	55	7
11	45	8	31	43	3
12	33	10	7	79	1
13	55	14	4	51	6
14	56	6	7	58	3
15	21	15	61	32	1

16	21	14	51	39	5
17	50	13	21	41	5
18	65	10	8	44	3
19	81	5	1	35	8
20	47	9	5	67	2
21	57	12	6	51	4
22	30	15	34	49	2

3.4.2. Better-Worse Coefficient Analysis

Better-Worse coefficient analysis method, refers to the method of calculating coefficients to quantitatively analyze the satisfaction of functional requirements, and obtain demand satisfaction indicators and dissatisfaction indicators, Better indicates that the user satisfaction improvement degree when the Mini Program has this function, the value is positive, the closer the value is to 1, the more satisfied the user is with the platform with this function, Worse indicates the user's dissatisfaction when the Mini Program does not have this function, the value is negative, the closer the value is to -1, the higher the user dissatisfaction level when the platform does not have this function, The calculation formula is as follows: Eq. (8) and Eq. (9).

$$Better(SI) = (A + O) / (A + O + M + I) \tag{8}$$

$$Worse(DIS) = -1 \times (M + O) / (A + O + M + I) \tag{9}$$

The better(si) value and worse(dis) value of functional requirements are plotted from Eqs. (8) and (9) and the results are shown in Table 10.

Table 10. Classification of functional requirements for jewelry design.

Functional requirement	SI	DIS
1	0.692	-0.046
2	0.287	-0.163
3	0.323	-0.331
4	0.31	-0.341
5	0.48	-0.224
6	0.448	-0.224
7	0.626	-0.089
8	0.39	-0.089
9	0.56	-0.192
10	0.39	-0.301
11	0.417	-0.307
12	0.333	-0.132
13	0.556	-0.145
14	0.488	-0.102
15	0.279	-0.5891
16	0.28	-0.52
17	0.504	-0.272
18	0.591	-0.142
19	0.705	-0.049
20	0.438	-0.109
21	0.548	-0.143
22	0.352	-0.383

The absolute value of worse(dis) in the table is used as the horizontal coordinate axis; the absolute value of better(si) is used as the vertical coordinate axis, and the average of the absolute values of better and worse is used as the origin of the coordinate axis, and the two-dimensional coordinate system is plotted as shown in Figure 10.

In the platform design, the function priority ranking is essential attributes>expected attributes charismatic attributes>non-differentiated attributes, in the actual market innovation, the expected attributes and charismatic attributes of the product in the market as a point of competition, which affects the user's satisfaction with the product, so this project will have expected attributes and charismatic attributes of the functional requirements of the design of the innovation point, including the user according to their personal preferences, independent selection of accessories Pearls with, according to personal diy generated products, the platform provides order production services, the platform provides jewelry 3d model display. According to the user's needs, the platform provides 1 to 1 customization service, according to the trend to provide style with reference product charts, shopping operation is smooth and simple, the elderly are also easy to operate, the platform provides users with jewelry design auctions and competitions channel, according to the user's needs to customize the page color and style, to enhance the jewelry personalized customization services.

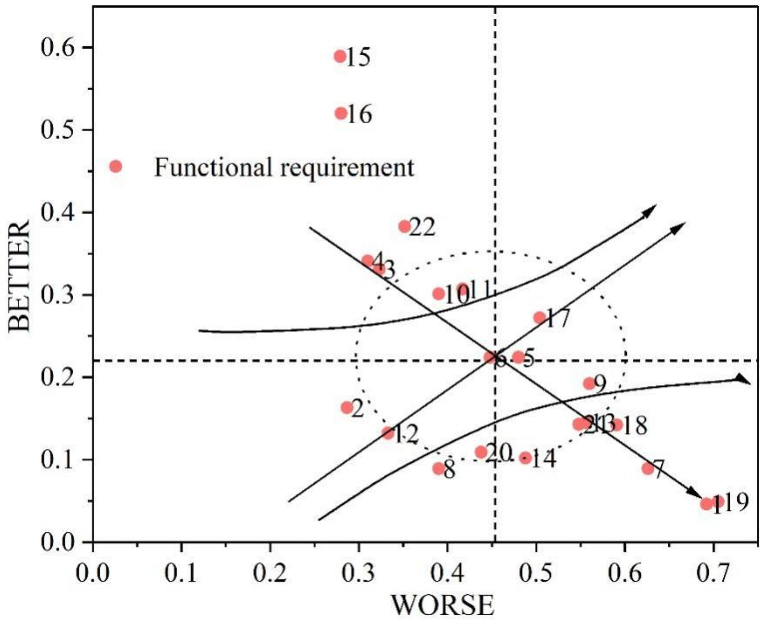

Figure 10. Quadrant diagram of better worse coeficient analysis.

4. Conclusion

This paper proposes an interactive genetic algorithm based on the user preference model, and in order to illustrate the performance of the algorithm, jewelry design books are selected as the research object and comparative experiments are conducted. The experimental results show that integrating the new attribute value preference into the current user preference information can effectively explore the potential user preferences, which is conducive to quickly tracking user preferences and accelerating the algorithm's convergence speed when user preferences change. Subsequently, 22 design functional requirements are proposed, which are divided into four functional attributes, and the functional design that conforms to the desired attributes and charismatic attributes is taken as the focus of jewelry design to improve the ability of personalized customization of jewelry design.

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