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Computer-Aided Design AND APPLICATIONS

Personalized Design of Tourism Products Based on Computer-Aided Strategy Driven by Big Data

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Abstract. This article analyzes the application value and potential advantages of big data in tourism product design. It explores the role and methods of CAD-assisted strategies in the personalized design of tourism products. On this basis, this article constructs a personalized design model for tourism products based on big data and CAD-assisted strategies. The feasibility and effectiveness of the model were verified through practical application and case analysis. Through comparative experiments, it was found that this method exhibits significant advantages in meeting the needs of tourists. Compared with traditional methods, this approach can more accurately grasp the needs and behavioural characteristics of tourists and provide personalized design solutions that better meet their needs. The above results indicate that the model is feasible and effective, providing strong support for the practice of personalized design of tourism products. This research result not only helps to improve the quality and competitiveness of tourism products but also provides new ideas for the development of the tourism industry.

Keywords: Big Data; CAD; Tourism Products; Personalized Design
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1 INTRODUCTION

With the rapid development of the global economy and the continuous improvement of living standards, tourism has gradually become a key industry worldwide. In addition, consumer demand for tourism products is becoming increasingly diverse, with a greater emphasis on the individuality and uniqueness of tourism products. With the rapid development of the tourism industry, the demand for travel experiences from users is constantly increasing. They not only focus on the destination of the trip but also on the quality and personalized experience of the trip. Therefore, how to provide users with high-quality tourism routes and recommendations has become an important issue. Markov chain, as a stochastic process model, can be used to solve the optimization and recommendation problems of travel routes. In travel route optimization and recommendation, Ahmad et al. [1] treat each event as a travel location or attraction, and the probability of an event occurring can be expressed as the probability of transitioning from one location to another. By calculating these transition probabilities, it can predict user behaviour and decisions during the travel process, providing them with personalized travel routes and recommendations. User-limited travel route optimization and recommendation refer to tailoring travel routes and recommendations to users based on their preferences and needs. These restrictions may include user travel time, budget, interests, and hobbies. By incorporating these constraints into the Markov chain model, we can better provide users with travel plans that meet their needs. Collaborative tourism information search is an information search method based on swarm intelligence. It uses the collaborative features of the Internet to integrate and classify information from different sources, helping users find the information they need faster and more accurately. Through this method, users no longer need to switch back and forth between numerous tourism websites, forums, blogs, and other platforms but can obtain all necessary information through a one-stop unified platform. Supporting online tourism planning is one of the core functions of collaborative tourism information search. Users can input their travel dates, budgets, interests, and other information on the platform, and the system will recommend suitable travel routes and activities to users based on this information. In addition, users can also communicate with other travellers on the platform, and share their travel experiences and suggestions, thereby further enriching and improving their travel plans [2]. The application of CAD-assisted strategy in tourism information retrieval aims to use computer-aided design technology to structurally process tourism information, making it easier to retrieve and utilize. Driven by big data, the importance of this strategy is increasingly prominent. Due to the massive and heterogeneous nature of tourism information in the big data environment, traditional information retrieval methods can no longer meet the needs of users. In traditional tourism information search, users often need to filter and organize information themselves, which is both time-consuming and laborious. On the other hand, collaborative query reconstruction optimizes queries by introducing collective intelligence and utilizing user search history, interest preferences, and other information to provide more accurate results. The advantage of this method is that it can fully utilize existing data resources, improve search efficiency, and provide users with more personalized information services [3]. This trend requires tourism companies to constantly update their product designs to meet the constantly changing needs of consumers.

The rise of big data technology provides new opportunities and challenges for the personalized design of tourism products. Big data technology can process massive amounts of data, and through data mining and analysis, one can gain a deeper understanding of consumer needs and behavioural characteristics. Data has become a key element in driving innovation and development in various industries. In the field of tourism product casting and manufacturing, CAD (computer-aided design) technology provides strong support for product design. Favi et al. [4] explored how to combine CAD-assisted strategies with the design of casting manufacturing methods for tourism products under the drive of big data. Big data technology can provide massive data support for the manufacturing of tourism product castings, helping enterprises better understand market demand, optimize product design, and improve production efficiency. It analyzes big data such as user behaviour and consumption habits, understands consumer needs and preferences for tourism products, and provides references for product design. It utilizes big data technology to analyze various data in the production process, identify potential improvement points, optimize process flow, and improve production efficiency. By collecting and analyzing quality data during the production process, real-time monitoring and prediction of product quality are carried out to promptly identify and solve problems. The integration of digital tourism and intangible cultural heritage may also bring some problems. On the one hand, commercial development may lead to excessive commercialization and distortion of intangible cultural heritage, affecting its authenticity and inheritance. On the other hand, digital technology may also exacerbate the impact of tourism on the local environment and community, such as the environmental pressure and cultural impact caused by the influx of tourists. Gonçalves et al. [5] have taken a series of measures. Firstly, it standardizes the development and protection of digital tourism and intangible cultural heritage. Secondly, it is necessary to increase public awareness and respect for intangible cultural heritage and to raise tourists' awareness of protection. In addition, we should strengthen scientific research cooperation and technological innovation, and improve the technological level of digital tourism and intangible cultural heritage protection. Their participation is crucial for achieving sustainable development. By establishing a reasonable profit distribution mechanism and cooperation model, local communities can play a positive role in digital tourism and intangible cultural heritage protection. Traditional tourism methods can no longer meet people's needs for deep experiences and personalized services. Immersive digital tourism has emerged in this context, providing tourists with a more authentic and in-depth travel experience through the presentation of multisensory clues. Guo et al. [6] discussed the role of multisensory cues in the experience of digital museums and further analyzed how the hotel and tourism industries can learn from this model to improve visitor satisfaction and loyalty. In digital museums, this experience is particularly prominent. This kind of interaction not only increases the fun of the exhibition but also helps to stimulate the creativity and imagination of tourists. In addition, big data technology can also help enterprises predict market trends, and lay out, and plan products in advance, thereby seizing market opportunities. However, big data technology has also brought challenges. Extracting valuable information from massive data and transforming this information into actual product design is a problem that needs to be solved. In addition, the implementation of big data technology also requires corresponding technical and talent support, which is also a challenge that tourism enterprises need to face.

CAD technology can help designers better realize their creativity and design intentions, and improve design efficiency and quality. The demand for personalized customized clothing among tourists is increasing day by day. Guo and Istake [7] aim to explore the evaluation of two-dimensional CAD technology for tourism body customization clothing based on CAD-assisted strategies under the drive of big data. The application of big data technology enables us to quickly process and mine large amounts of data, thereby more accurately grasping market dynamics and consumer demands. In the field of tourism clothing customization, big data can help enterprises understand the physical characteristics and wearing habits of tourists, providing data support for personalized customization. As the foundation of modern fashion design, CAD technology can help designers quickly create design sketches, and accurately measure dimensions and design patterns. In customized tourist clothing, CAD technology can greatly improve production efficiency and meet the personalized needs of tourists. With the booming development of the tourism industry, tourists have increasingly diverse and personalized demands for itinerary planning. The system provides tourists with more targeted and flexible itinerary planning services by updating and integrating scenic area information in real time. The core of this system lies in the real-time collection and processing of dynamic information about tourist attractions. By connecting with the information interfaces of various scenic spots, the system can obtain key information such as real-time passenger flow, opening hours, and weather conditions of the scenic spots. These pieces of information are crucial for itinerary planning as they directly affect the tourist experience and itinerary arrangements, the system will advise tourists to adjust their itinerary to avoid peak hours, thereby improving travel comfort and efficiency [8]. Through CAD technology, designers can quickly create and modify design drawings, renderings, and 3D models to better meet the personalized needs of consumers for tourism products. In summary, this study aims to combine big data with CAD technology to construct a personalized design model for tourism products. By utilizing big data technology to deeply explore and analyze consumer needs and behavioural characteristics, combined with CAD technology, design efficiency and quality can be improved, thereby enhancing the market competitiveness of tourism products. This study will not only promote innovative development in the tourism industry but also provide useful references for personalized design in other industries. Its innovation is mainly reflected in the following aspects:

(1) Methodology innovation: This article combines big data and CAD technology to build a brand-new Personalized Design model for tourism products. This methodological innovation makes the design of tourism products more accurate and efficient and can better meet the increasingly diverse needs of consumers.

(2) Technological application innovation: Through big data technology, in-depth exploration and analysis of consumer needs and behavioural characteristics is an innovative practice of applying big data technology in the tourism industry. In addition, combining CAD technology to improve design efficiency and quality is also a new application of CAD technology in tourism product design.

(3) Combination of theory and practice: This article not only theoretically discusses the Application of big data and CAD in the Personalized Design of tourism products but also proves its feasibility and effectiveness through practical cases and practices. This close combination of theory and practice is a major innovation of this article.

The main issue of this study is how to combine big data with CAD technology to construct a personalized design model for tourism products. To address this issue, this study adopted a combination of theoretical analysis and empirical research, including literature review, model construction, application practice, and effectiveness evaluation. The technical roadmap is as follows: Firstly, through literature review, understand the current application status and development trends of big data and CAD technology in tourism product design. Secondly, based on actual needs and existing technology, a personalized design model for tourism products was constructed using big data and CAD technology. Then, the feasibility and effectiveness of the model were verified through practical application and case analysis. Finally, the research results were summarized, and suggestions and prospects for future research were proposed.

2 THEORETICAL BASIS

In the processing of CAD models, neutral re-import and exchangeable persistent identifiers are two important concepts. Jauhar et al. [9] explored how to use tourism products' exchangeable persistent identifiers in computer-aided design of tourism products to achieve more efficient and accurate design processes. Neutral re-import is a method of ensuring the lossless transfer of CAD models between different software platforms. By converting CAD models to intermediate formats, model sharing and exchange can be achieved between different CAD software. This format is independent of any specific CAD system, allowing designers to freely switch between different CAD software, improving design flexibility and efficiency. In the processing of CAD models, due to the complexity and dynamism of the model, the unique identification and tracking of model elements become particularly important. EPID provides a persistent and interchangeable identifier for CAD model elements, ensuring accurate identification and processing between different software and systems. Downstream computer-aided design refers to the Application of CAD in subsequent stages, such as manufacturing and processing after the completion of product design. At this stage, it is necessary to ensure the accuracy and consistency of upstream design data so that downstream processes can be implemented smoothly. By using exchangeable tourism product persistent identifiers in neutral re-import, data consistency and accuracy in the tourism product process can be ensured, improving production efficiency and quality. With the rapid development of artificial intelligence technology, its application in tourism product design is becoming increasingly widespread. Among them, the computer-aided engineering (CAE) method based on multi-view classification has become an effective way to significantly improve the efficiency and quality of tourism automation product design. Krahe et al. [10] focused on exploring the CAE method for tourism automation product design based on artificial intelligence. The view classification method is a method of decomposing product design problems into multiple related views. Each view describes product design issues from different perspectives, providing more comprehensive information. In the field of tourism automation product design, multi-view classification methods can decompose product design problems into multiple views such as functionality, users, technology, etc. Each view has its own specific classification and optimization methods. Take an online travel company as an example. The company hopes to design a travel automation product that can meet the needs of different users. By adopting a multi-view classification-based CAE method, the company has successfully designed a tourism automation product that meets user needs and has achieved a good market response. With the booming development of the tourism industry, tourists have increasingly diversified and personalized demands for itinerary planning. To meet this demand, Lavorel et al. [11] analyzed the emergence of a personalized, on-site itinerary design and planning support system based on dynamic information about tourist attractions. The system provides tourists with more targeted and flexible itinerary planning services through real-time updates and integration of scenic spot information. The core of this system lies in the real-time acquisition and processing of dynamic information about tourist attractions. By connecting with the information interfaces of various scenic spots, the system can obtain key information such as real-time passenger flow, opening hours, and weather conditions of the scenic spots. These pieces of information are crucial for itinerary planning as they directly affect the tourist experience and itinerary arrangements. Tourists only need to input basic information such as the attractions they are interested in, travel time, and budget, and the system will generate multiple itinerary plans that meet their needs. These plans not only take into account the dynamic information of scenic spots but also refer to the evaluations and feedback of other tourists to ensure the quality and satisfaction of the itinerary.

In the field of tourism, 3D CAD systems can provide a new method for the design and planning of tourism systems. Liu [12] discussed the rapid design method and application of a tourism system recommendation program based on a 3D CAD system. A 3D CAD system is a tool that utilizes computer technology for 3D model design and simulation. It can provide an intuitive and three-dimensional design interface, allowing designers to more accurately express design intentions and improve design efficiency. In the design of tourism systems, 3D CAD systems can simulate the terrain, landforms, buildings, facilities, etc. of tourist attractions, providing strong support for the planning and design of tourism systems. By utilizing the simulation function of 3D CAD systems, real-time evaluation and optimization of design schemes can be carried out. After completing the detailed design, the design plan can be used as a construction drawing output for the construction and operation of the scenic area. Meanwhile, the 3D CAD system can also provide support for the later management and maintenance of scenic spots. Augmented reality technology has demonstrated its unique value in various fields. Fuzzy weight, as an important decision analysis method, can be used to personalize the learning path of tourists in this situation. Fuzzy weight is a weight determination method based on fuzzy set theory, which can handle various situations of uncertainty, fuzziness, and incomplete information. In augmented reality tourism products, fuzzy weights can be used to measure the attractiveness of various tourism resources, facilities, services, etc. to tourists, thereby providing a foundation for the development of personalized learning paths. Based on this weight information, Papakostas et al. [13] recommended personalized learning paths for tourists. For tourists who enjoy natural landscapes, the application can recommend tourist routes that focus on natural landscapes. For tourists interested in history and culture, this application can recommend routes to visit historical sites. This personalized recommendation not only improves tourist satisfaction but also enables more rational utilization of tourism resources.

The traditional two-dimensional design method can no longer meet the complexity and refinement requirements of modern tourism product design. The applicability of 3D factory simulation software as an advanced computer-aided design tool in computer-aided participatory design of tourism product workplaces and processes is worth exploring. 3D factory simulation software can create highly realistic 3D virtual environments and provide realistic visual effects. Designers can perform factory layout, equipment configuration, logistics planning, and other operations in a virtual environment to evaluate the effectiveness and feasibility of design solutions. In addition, the software also has a real-time simulation function, which can simulate the factory operation process and provide designers with real-time feedback and optimization suggestions. The workplace and process design of tourism products involves knowledge in multiple fields such as ergonomics, logistics management, and environmental control. Designers need to consider various factors comprehensively to ensure that the design scheme not only meets production needs but also provides a good user experience. However, traditional two-dimensional design methods are unable to fully reflect the complexity of actual workplaces and processes, resulting in low design efficiency and resource waste [14]. Traditional tourism experiences can no longer meet the needs of modern tourists, and digital tourism experiences based on CAD-assisted strategies are gradually becoming a new trend. Preko et al. [15] explored how this big data-driven experience model can provide tourists with more personalized and convenient travel services. Through big data technology, tourism enterprises can deeply explore information such as tourist behaviour habits, interests, preferences, and consumption abilities, thereby providing customers with more accurate and personalized services. At the same time, combined with event planning, tourism companies can recommend suitable travel routes and activities for tourists based on their needs and time arrangements, improving their satisfaction and loyalty. The core of the digital tourism experience lies in providing tourists with more authentic, convenient, and creative tourism experiences through digital technology. Driven by big data, this experience model has been further upgraded and improved. Through data analysis and simulation techniques, tourists can gain a deeper understanding and plan for tourist attractions before departure, avoiding unnecessary trouble and wasting time during the journey.

With the prosperous development of the tourism industry, the demand for tourism product design is also increasing day by day. As an important part of tourism product development, the Application of process simulation in industrial design is of great significance for improving design efficiency and product quality. Staszak [16] explored process simulation methods in the industrial design of tourism products based on CAD-assisted strategies to promote the innovative development of tourism products. Using CAD software for design modelling can quickly create complex 3D models, making it convenient for designers to modify and optimize. Through the simulation analysis function of CAD software, the structure of tourism products can be analyzed for stress and vibration, ensuring the stability and reliability of the products. By importing CAD models into CAM (Computer Aided Manufacturing) software, rapid prototyping and mass production of tourism products can be achieved. Through the rapid modelling function of CAD software and the real-time analysis ability of process simulation software, designers can obtain design feedback and optimize it more quickly. Process simulation methods can identify potential design issues in the early stages, avoid later modifications and rework, and reduce development costs. Through precise process simulation analysis, it can be ensured that the performance and quality of tourism products meet design requirements. In the tourism industry, applying Internet information technology and deep learning to tourism collaborative recommendation systems can provide tourists with more personalized and accurate tourism recommendation services, improving the tourism experience. Wang [17] analyzed the Application of Internet information technology in tourism collaborative recommendation systems. It is mainly reflected in data acquisition, processing, and analysis. Through the Internet, a vast amount of tourism-related information can be obtained, including attraction introductions, user reviews, travel guides, and more. These data, after processing and analysis, can be used to train deep learning models and further explore user preferences and needs. The Application of deep learning in tourism collaborative recommendation systems is mainly based on its powerful feature learning and pattern recognition capabilities. By training deep neural networks, effective features can be automatically extracted from the data, and recommendations can be made based on these features. Compared with traditional collaborative recommendation algorithms, deep learning can more accurately grasp user preferences and needs, improving recommendation accuracy.

Wang [18] proposed a personalized recommendation-based online tourism framework design, aiming to achieve personalized design and recommendation of tourism products through industry management and data systems. The core of a personalized recommendation framework lies in the precise grasp of user needs and the personalized design of tourism products. By collecting data on user interests, preferences, and historical behaviours, and using advanced algorithms for analysis, we can gain a deeper understanding of user needs and psychological expectations. On this basis, personalized designs and recommendations are made based on the characteristics and market trends of tourism products. Industrial management and data systems are key components in achieving personalized recommendations. By establishing a comprehensive management system, integrating resources from all parties, and achieving data sharing and exchange. In short, the design of personalized recommendation frameworks for online tourism is an important trend for the future development of the tourism industry; By effectively integrating industry management with data systems, personalized design and recommendation of tourism products can be achieved, enhancing user experience and market competitiveness. Tourism product design is also facing increasing personalized needs. Meeting the needs of different consumers and providing personalized tourism products has become an important challenge facing the tourism industry. Yang and Lee [19] explored how to use computational design methods to understand the personalization of tourism product design, and proposed an effective tourism product design method based on practical insights into the perception of tourism consumers. It collects a large amount of data about tourism consumers, including behaviour, preferences, needs, etc. These data can be obtained through online surveys, user feedback, data analysis, and other means. Extract features related to tourism product design from the collected data, such as attraction types, accommodation preferences, travel methods, etc. Build predictive models using machine learning and other technologies. These models can automatically generate personalized tourism product design solutions based on the characteristics and needs of consumers. The field of tourism planning is undergoing profound changes. Traditional tourism planning methods are no longer able to meet the diverse and rapidly changing demands of the market. The application of big data has brought new opportunities for process innovation and team collaboration in tourism planning. Yeh and Ku [20] will explore the innovation capability and subsequent team collaboration performance of the tourism planning process driven by big data from the perspective of knowledge exchange platforms. Big data has brought unprecedented data resources and processing capabilities to tourism planning, making process innovation possible. This data-driven process innovation not only improves the accuracy and effectiveness of planning but also makes the planning process more scientific and transparent.

3 CONSTRUCTION OF PERSONALIZED DESIGN MODEL OF TOURISM PRODUCTS

3.1 Ideas and Principles of Model Design

CAD is a technical tool that uses computers to facilitate design creation. In the field of tourism product design, the application of CAD technology is mainly reflected in several key areas:

(1) Design performance: CAD technology can help designers quickly generate design drawings, renderings, and three-dimensional models and improve the quality and efficiency of design performance.

(2) Structural design: CAD technology can help designers carry out accurate size measurement, component assembly, and structural optimization, as well as improve the structural performance and stability of products.

(3) Selection of materials and processes: CAD technology can help designers select and optimize materials and processes and improve the quality and life of products.

(4) Cost budget: CAD technology can help designers carry out accurate cost budgets and control and improve the economic benefits and market competitiveness of products.

Personalized design refers to a customized design method that meets the specific needs and attributes of users. Its basic principles revolve around prioritizing user satisfaction, emphasizing the uniqueness and personalization of the product, and ensuring its practicality and functionality. The methods of personalized design include user research, prototype design, iterative optimization, and customized production. In the design of tourism products, the application of personalized design is mainly reflected in providing tourists with a more intimate and personalized travel experience based on their needs and behavioural characteristics.

Big data has 4V characteristics, namely capacity, speed, diversity, and value. In the tourism industry, the application of big data is mainly reflected in market analysis, tourist behaviour analysis, product development, and innovation. By mining and analyzing massive amounts of data, we can gain a deeper understanding of the needs and behavioural characteristics of tourists, providing more accurate and personalized guidance for tourism product design. In recent decades, CAD technology has made significant progress in tourism product design, highlighting its applications in 3D modelling, rendering, and virtual reality. The case study demonstrates the enormous potential of CAD in this field.

Nonetheless, integrating big data with CAD for personalized tourism product design remains uncommon. This study aims to bridge this knowledge gap, offering fresh perspectives and techniques. By merging big data and CAD in tourism product design, we can accomplish several objectives:

(1) Quick acquisition of tourist preferences: Big data analysis quickly reveals tourist needs and behaviours, guiding more accurate product design.

(2) Streamlined Design Workflow: CAD tools expedite the creation of drawings, renderings, and 3D models, enhancing both quality and efficiency. Additionally, they aid in precise measurements, component assembly, structural optimization, and overall product stability.

(3) Enhancing market competitiveness: Integrating big data and CAD to meet the needs of tourists better, enhancing the uniqueness and personalization of products. This method also helps with cost control, productivity, and overall market competitiveness. It is crucial to clarify design concepts and adhere to key principles in developing personalized design models for tourism products. Design concepts are the foundation of a model, determining its functionality and defining features. The use of big data technology can extract and analyze large datasets, promote a deeper understanding of consumer preferences and behaviours, and provide information for personalized design decisions. CAD technology supplements this process by helping designers more effectively achieve their creative vision and design intentions, thereby improving the efficiency and quality of the design process. Therefore, the integration of big data and CAD technology has paved the way for personalized tourism product design, catering to the constantly changing and diverse preferences of consumers.

In addition, certain principles should be followed when building the model. Firstly, the model should be efficient and capable of quickly processing large amounts of data and generating personalized design solutions. Secondly, this model should be practical, meet the needs of practical applications, and provide effective support and services for tourism enterprises. Third, the model should be extensible, able to adapt to changing market demands and technological development, and constantly optimize and improve. Finally, the model should be user-friendly, easy to use and maintain, and reduce the difficulty and cost of user operation. Adhere to these principles to ensure that the customized design mode of tourism products not only timely meets market demand and personalized user requirements but also improves design efficiency, quality, and overall market competitiveness of the product. In addition, the continuous optimization and enhancement of this model is consistent with the constantly developing market trends and technological progress, providing strong support for the innovative growth of the tourism industry.

3.2 The Overall Architecture and Functional Modules of the Model

When constructing a customized design model for tourism products, its architecture includes four different layers: data collection layer, data processing layer, design assistance layer, and application layer. As the cornerstone of the model, the data collection layer collects a series of comprehensive data related to tourism products. This diverse dataset includes user behaviour data, market trends, product details, and more. This collection work can thoroughly understand consumer preferences and market changes and ensure the initial cleaning and organization of data to maintain its accuracy and completeness. The data processing layer is one of the core parts of the model, responsible for further processing and processing the collected data. Firstly, the data processing layer will clean and integrate the data to remove invalid and abnormal data. Then, through a series of data analysis and mining techniques, valuable information is extracted to provide data support for a personalized design. These technologies include statistical analysis, generating adversarial networks, and so on.

In this study, the refinement of the discriminator D is addressed independently. Essentially, the training of the discriminator D aims to reduce the cross entropy between its anticipated and genuine outputs. Consequently, the loss function specific to the discriminator can be delineated as follows:

$$L_D\left(\theta_D,\theta_G\right)=-\frac{1}{2}E_{x\sim P_{data}(x)}\left[\log D(x)\right]-\frac{1}{2}E_{Z\sim P_z(z)}\left[\log\left(1-D(g(x))\right)\right] \tag{1}$$

In this context, x it denotes actual data that aligns with the distribution of genuine data P_{data}. z Represents the arbitrary noise inputted into the generator G, adhering to the preset distribution

$P_z(z)$. $E(\cdot)$ It is indicative of the anticipated value. With the generator G remaining constant, minimizing the aforementioned formula yields the most favourable outcome. Assuming continuity in the function, the formula can be reformulated as follows own below:

$$\begin{aligned} L_D(\theta_D,\theta_G) &= -\frac{1}{2}\int_x P_{data}(x)\log(D(x))dx - \frac{1}{2}\int_z P_z(z)\log(1-D(g(z)))dz \\ &= -\frac{1}{2}\int_x \left[P_{data}(x)\log(D(x)) + p_g(x)\log(1-D(x))\right]dz \end{aligned} \tag{2}$$

For any nonzero real number a and any real number b, given that the real number y falls within the range of 0 to 1, the formula reaches its minimum point $\frac{a}{a+b}$, as described below:

$$-a\log(y) - b\log(1-y) \tag{3}$$

Hence, when the generator G is specified, the discriminator D's loss function attains its minimum value as expressed in the subsequent formula, constituting the most favourable outcome under these circumstances:

$$D_G^*(x) = \frac{P_{data}(x)}{P_{data}(x)+P_g(x)} \tag{4}$$

The formula objective for GAN is presented as follows:

$$\min_G \max_D V(D,G) = E_{x-P_{data}}\left[\log D(x)\right] + E_{z-P_z}\left[\log(1-D(G(z)))\right] \tag{5}$$

The training procedure can be perceived as an adversarial contest between the generator and the discriminator. In this game, the discriminator strives to reduce the cross entropy between its actual and expected outputs. Meanwhile, the generator's goal is to increase the likelihood $D(G(z))$ that the discriminator will classify its generated samples as "real data" based on feedback. Once this occurs, both the generator and discriminator undergo a round of parameter adjustment. Over multiple rounds of feedback and updates, the generator and discriminator eventually achieve a Nash equilibrium, resulting in generated samples that closely match the distribution of real data.

The design assistance layer is a key part of achieving personalized model design. It utilizes CAD technology to personalize the design of tourism products based on the information provided by the data processing layer. Designers can use CAD software for modelling and rendering at this level, effectively achieving creativity and design intent. In addition, the design assistance layer can also adjust and optimize the design scheme based on user feedback and actual needs. The application layer is a crucial step in applying design results to practice. At this level, the designed tourism product plan can be generated, implemented, and launched into the market. Through continuous optimization and improvement, the personalization and market competitiveness of tourism products can be further enhanced. In addition, this model can be continuously optimized and improved according to market demand and technological development, providing strong support for the innovative development of the tourism industry. The GAN model used for product feature learning is shown in Figure 1.

To enable the personalized design of tourism products, the model's functional modules must encompass a range of capabilities, including data gathering, storage, analysis, CAD design, and user feedback. These modules work together seamlessly to facilitate the customized design process. The data acquisition module is tasked with aggregating diverse data pertinent to tourism products, such as user behaviour patterns, market trends, and competitor information. This data serves as a crucial foundation for subsequent analytical processes and personalized design efforts. The data storage module securely manages and preserves the collected data, employing efficient technologies to ensure its reliability and scalability. It also incorporates robust access controls and security measures to safeguard data integrity and privacy.

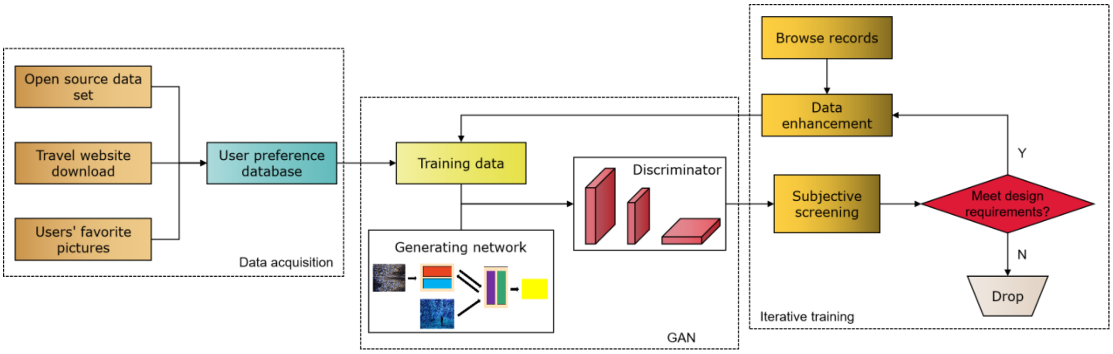

Figure 1: Product feature learning model.

The data analysis module delves deeply into the stored data, leveraging statistical analysis and machine learning techniques to process user behaviour and market trend insights. This analysis reveals valuable information about user preferences and needs, guiding the personalization of designs. Furthermore, the module can forecast future market demands and competitive landscapes, aiding in strategic decision-making. The CAD design module stands at the heart of the personalization process. It incorporates CAD tools to craft bespoke tourism products based on the insights gleaned from the data analysis module. Designers can unleash their creativity within this module, utilizing CAD software for modelling, rendering, and refining designs. Furthermore, the module includes user feedback loops, enabling iterative enhancements to the design by incorporating real-time user input and practical factors. By positioning the projection centre at the image's midpoint, the corresponding coordinate values of the point A in the user display area, relative to the centre of the image in that area, align with its respective coordinates within the image coordinate system:

$$A = x - lWidth / 2, y - lHeight / 2 \tag{6}$$

In this context, x,y it represents the coordinate of the point A within the user area, $lWidth$ denotes the length of the image, and $lHeight$ signifies its height. To enhance accuracy and minimize errors in mouse selection when determining the coordinates of image points in the user area, a method involving multiple selections and subsequent averaging is employed. The formula utilized for this purpose is as follows:

$$x,y = \left(\sum_{i=1,n} x_i / n, \sum_{i=1,n} y_i / n \right) \tag{7}$$

The variational automatic encoder's fundamental concept outlines the algorithm's objective: acquiring a set of encoders and decoders that establish a bidirectional mapping between graph G and latent variable $z \in R^c$. The loss function for the graph variational automatic encoder is subsequently defined in the following manner:

$$L \; \varphi,\theta;G = E_{q_\varphi \; z|G} \left[-\log p_\theta \; G|z \right] + KL\left[q_\varphi \; z|G \, \middle| \, p \; z \right] \tag{8}$$

Within this context, the initial $E_{q_\varphi \; z|G} \left[-\log p_\theta \; G|z \right]$ represents the reconstruction loss, guaranteeing the resemblance between the generated and input graphs. Meanwhile, the second component, KL

divergence, ensures that the vector z is sampled directly from the distribution $p(z)$. The maximum likelihood estimation for each graph observation can be broken down into:

$$-\log p(G|z) = -\lambda_A \log p(A|z) - \lambda_F \log p(F|z) \tag{9}$$

Because graph structures are inherently flexible, the data they generate may deviate from a rigid node order, leading to complexities in loss function calculations. To mitigate this issue, evasion methods are used during training, ensuring smooth and uninterrupted loss function calculations while also aiding in the backward propagation of parameter gradients.

The user feedback module is an indispensable part of the model. This module iteratively optimizes and improves the design scheme by collecting users' feedback and suggestions on the design scheme. User feedback can be obtained through online surveys, user interviews, etc. This module collates and analyzes users' opinions and suggestions and provides them to designers and data analysts for targeted optimization of design schemes.

The data is acquired by a data acquisition module and stored and managed by a data storage module. The data analysis module deeply analyzes and mines the data and extracts valuable information; the CAD design module uses this information to carry out Personalized Design. Finally, the user feedback module collects user feedback and iteratively optimizes the design scheme. Through this series of processes, the Personalized Design of tourism products can be realized efficiently, the diversified needs of users can be met, and market competitiveness can be improved.

3.3 Integration and Optimization of the Model in the CAD System

Integrating the model seamlessly with the CAD system maximizes their respective strengths, enhancing both the efficiency and quality of personalized tourism product design. This integration facilitates features like data sharing, automated processes, and collaborative design, all of which contribute significantly to streamlining Personalized Design workflows.

To achieve this integration, either an API interface or a plug-in can be utilized. The API interface enables the model to access the CAD system's functions and data, facilitating effortless data exchange and process automation. Additionally, it offers a wealth of customization options tailored to the unique requirements of personalized design. Alternatively, the plug-in approach is another popular integration method. By developing plug-ins compatible with the CAD system, the model's functionalities can be smoothly integrated, providing designers with a convenient platform for carrying out customized designs.

In terms of optimization, the CAD system can be tailored to align with the specific needs of Personalized Design. By leveraging the data and functional requirements provided by the model, the CAD system can undergo custom modifications that optimize its interface, features, and operational flow. This customized development significantly boosts designers' productivity and elevates the overall quality of their designs.

To enhance the system's stability and efficiency, optimizing the CAD system's performance and upgrading its technology is imperative. Employing high-performance computing and distributed storage technologies can bolster the system's data processing capabilities and accelerate its response time. Furthermore, incorporating cache technology and load-balancing techniques can fine-tune the system's performance and stability.

4 APPLICATION AND PRACTICE OF THE MODEL

4.1 Case Study on the Application of the Model in Tourism Product Design

In order to rigorously validate the model, this article selected a series of representative tourism product design cases for in-depth analysis. Taking the design of a famous scenic spot as an example, a large amount of tourist behaviour data and market survey data were first collected. In the data analysis stage, use this model to mine and analyze the collected data deeply. Identify the themes and trends of tourist demand, as well as the behavioural patterns and preferences of tourists in scenic areas, through statistical analysis, generation of adversarial networks, and other methods. These analysis results provide important guidance for the design of personalized tourism products in the future. Based on the analysis of the results, this article adopts a CAD system for the design of personalized tourism souvenirs. In the design, the needs of tourists were fully considered.

In practical Application, the effectiveness of this method is further verified through communication and feedback with tourists. Many tourists said that the design of tourist souvenirs paid more attention to their needs and experiences, which made them feel more happy and satisfied during the tour.

4.2 Effect Assessment and Optimization of the Model in Practice

In order to evaluate the actual effectiveness of the model, this article adopts a series of methods to evaluate and optimize it. Firstly, through comparative experiments, compare the differences in design effectiveness and user satisfaction before and after adopting the model. The design effects before and after adopting this model are shown in Figures 2 and 3.

Figure 2: Design effect before adopting the model.

Figure 3: The design effect after adopting the model.

Secondly, the advantages and disadvantages of different design schemes are compared and selected by means of A/B testing. Finally, according to user feedback and actual use, the model is iteratively optimized and improved, which improves the performance and stability of the model. The model accuracy before and after iterative optimization is shown in Figure 4 and Figure 5.

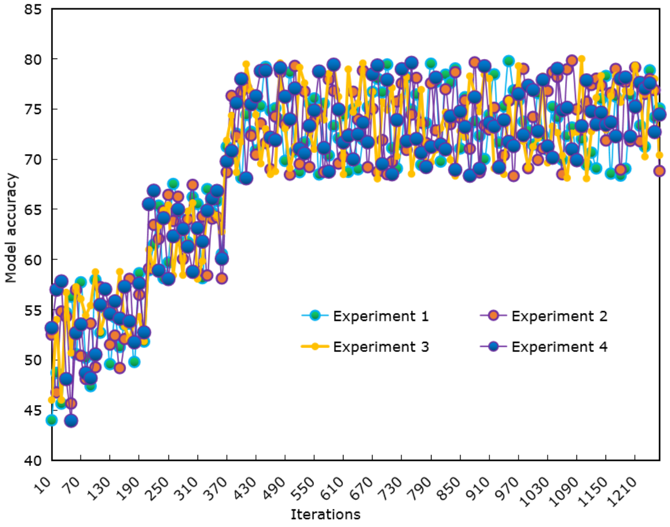

Figure 4: Model accuracy before iterative optimization.

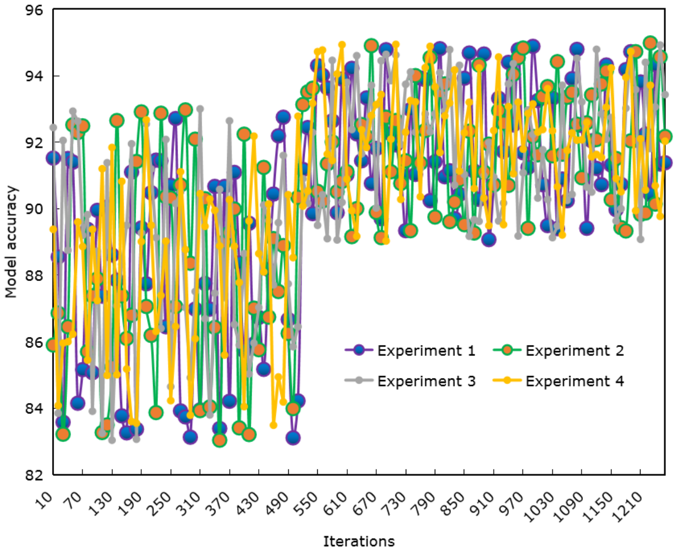

Figure 5: Accuracy of the model after iterative optimization.

The model stability before and after iterative optimization is shown in Figure 6 and Figure 7. To objectively and accurately evaluate the model's effectiveness, this article employs a comparative experimental approach. In this experiment, two sets of design schemes are chosen: one utilizing traditional design methods (serving as the control group) and the other incorporating the model (serving as the experimental group). Throughout the experiment, both groups undergo thorough evaluations and comparisons. The evaluation criteria focus on tourists' satisfaction, loyalty, and overall tour experience, with the findings presented in Table 1.

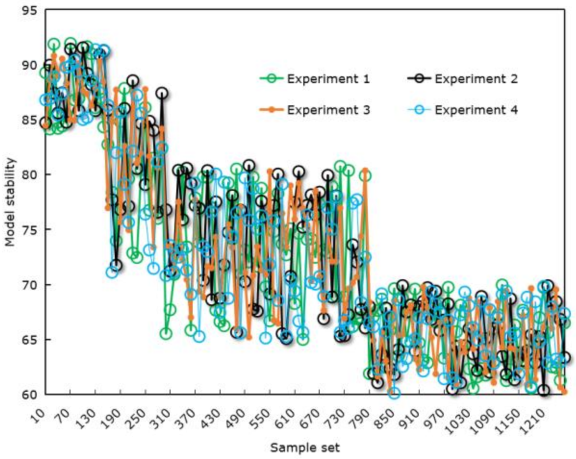

Figure 6: Model stability before iterative optimization.

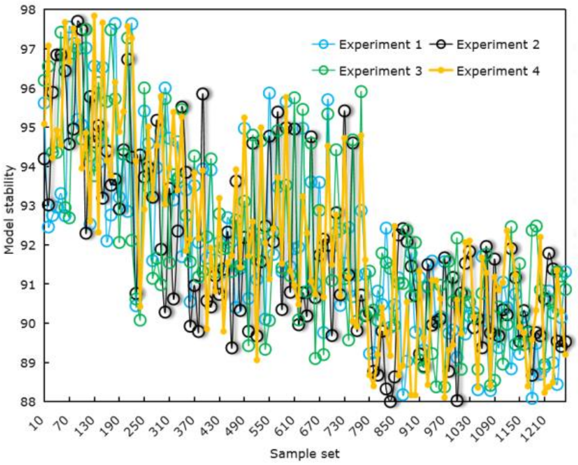

Figure 7: Model stability after iterative optimization.

Assessment index	Experimental group (using model)	Control group (traditional design)
Tourist satisfaction	92.48%	70.53%
Tourist loyalty	89.97%	60.89%
Tourist experience (average rating)	4.5/5 (Very good)	3.1/5 (Indifferently)

Table 1: Comparative experimental results.

In Table 1, detailed numerical data and metrics are presented for each evaluation criterion. Tourist satisfaction is quantified as a percentage, with the experimental group achieving 92.48% and the control group attaining 70.53%. Likewise, tourist loyalty is gauged using a percentage scale, where the experimental group scores 89.97% and the control group scores 60.89%. The overall tour experience is assessed using an average rating system. Specifically, the experimental group earns an average score of 4.5 out of 5, indicating excellence, while the control group receives an average score of 3.1 out of 5, suggesting indifference.

The survey results show that most users are satisfied with the tourism products designed by the model and think that the product design is more intimate and personalized, which can better meet their own needs. Moreover, users also put forward some valuable opinions and suggestions, which provided a useful reference for further optimization of the model.

4.3 Popularization Value and Prospect Analysis of the Model in the Tourism Industry

Based on the practical applications and analyses mentioned earlier, it becomes evident that the model possesses significant promotional worth and holds promising applications in the tailored design of tourism products. Firstly, enterprises can leverage this model to gain deeper insights into tourists' preferences and behavioural patterns, thereby enhancing the market competitiveness of their products. Secondly, the model proves beneficial in reducing product development timeframes, leading to improved design efficiency and superior quality. Lastly, the model contributes to bolstering enterprises' digital transformation and innovation capabilities, ultimately driving the overall industry's growth and advancement. Looking ahead, as big data technology continues to evolve and mature, the prospects for this model's Application become even more extensive.

5 CONCLUSION AND PROSPECT

In this research, an innovative model for personalized tourism product design is introduced, leveraging big data and CAD technology. This model not only facilitates customized designs but also bolsters market competitiveness. Key findings include the introduction of a data-driven design approach and the implementation of a comprehensive model encompassing data gathering, processing, analysis, and design assistance functions. Through hands-on applications and case studies, the model's feasibility and impact have been confirmed, leading to enhanced market competitiveness for tourism offerings.

The model's influence on the tourism sector is multifaceted: it steers product design towards greater personalization, catering to the diverse preferences of travellers; it elevates the market standing of tourism products, unlocking new business prospects for industry players; and it spurs digital transformation and innovation within the tourism industry, pushing forward its overall growth and evolution.

While significant progress has been made, there are areas for further refinement. Notably, expanding the range of data sources and types would enrich the model's capabilities. Moreover, future research could explore integrations with cutting-edge technologies like artificial intelligence and virtual reality, broadening the model's scope and potential.

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REFERENCES

[1] Ahmad, S.; Ullah, I.; Mehmood, F.: A Stochastic approach towards travel route optimization and recommendation based on users constraints using Markov chain, IEEE Access, 7(10), 2019, 90760-90776. https://doi.org/10.1109/ACCESS.2019.2926675

[2] Arif, A.; Du, J.-T.: Understanding collaborative tourism information searching to support online travel planning, Online Information Review, 43(3), 2019, 369-386. https://doi.org/10.1108/OIR-05-2017-0141

[3] Du, J.-T.; Mohammad, A.-A.-S.; Hansen, P.: Collaborative query reformulation in tourism information search, Online Information Review, 43(7), 2019, 1115-1135. https://doi.org/10.1108/OIR-12-2018-0371

[4] Favi, C.; Mandolini, M.; Campi, F.: A CAD-based design for manufacturing method for casted components, Procedia CIRP, 100(4), 2021, 235-240. https://doi.org/10.1016/j.procir.2021.05.061

[5] Gonçalves, A.-R.; Dorsch, L.-L.-P.; Figueiredo, M.: Digital tourism: an alternative view on cultural intangible heritage and sustainability in Tavira, Portugal, Sustainability, 14(5), 2022, 2912. https://doi.org/10.3390/su14052912

[6] Guo, K.; Fan, A.; Lehto, X.; Day, J.: Immersive digital tourism: the role of multisensory cues in digital museum experiences, Journal of Hospitality & Tourism Research, 47(6), 2023, 1017-1039. https://doi.org/10.1177/10963480211030319

[7] Guo, S.; Istook, C.-L.: Evaluation of 2D CAD technology for garments customized for body shape, Fashion Practice, 15(1), 2023, 136-162. https://doi.org/10.1080/17569370.2021.1987647

[8] Hidaka, M.; Kanaya, Y.; Kawanaka, S.; Matsuda, Y.; Nakamura, Y.; Suwa, H.; Yasumoto, K.: On-site trip planning support system based on dynamic information on tourism spots, Smart Cities, 3(2), 2020, 212-231. https://doi.org/10.3390/smartcities3020013

[9] Jauhar, T.-A.; Han, S.; Kwon, S.: Downstream computer-aided design, engineering, and manufacturing integration using exchangeable persistent identifiers in neutral re-imported computer-aided design models, Journal of Computing and Information Science in Engineering, 21(1), 2021, 014501. https://doi.org/10.1115/1.4047484

[10] Krahe, C.; Iberl, M.; Jacob, A.: AI-based computer-aided engineering for automated product design - a first approach with a multi-view based classification, Procedia CIRP, 86(7), 2019, 104-109. https://doi.org/10.1016/j.procir.2020.01.038

[11] Lavorel, S.; Grigulis, K.; Richards, D.-R.: Templates for multifunctional landscape design, Landscape Ecology, 37(3), 2022, 913-934. https://doi.org/10.1007/s10980-021-01377-6

[12] Liu, F.: Fast Industrial product design method and its Application based on 3D CAD system, Computer-Aided Design and Applications, 18(S3), 2020, 118-128. https://doi.org/10.14733/cadaps.2021.S3.118-128

[13] Papakostas, C.; Troussas, C.; Krouska, A.; Sgouropoulou, C.: Personalization of the learning path within an augmented reality spatial ability training application based on fuzzy weights, Sensors, 22(18), 2022, 7059. https://doi.org/10.3390/s22187059

[14] Pelliccia, L.; Bojko, M.; Prielipp, R.: Applicability of 3D-factory simulation software for computer-aided participatory design for industrial workplaces and processes, Procedia CIRP, 99(10), 2021, 122-126. https://doi.org/10.1016/j.procir.2021.03.019

[15] Preko, A.; Amoako, G.-K.; Dzogbenuku, R.-K.; Kosiba, J.: Digital tourism experience for tourist site revisit: an empirical view from Ghana, Journal of Hospitality and Tourism Insights, 6(2), 2023, 779-796. https://doi.org/10.1108/JHTI-10-2021-0294

[16] Staszak, M.: Process simulation approach in computer-aided industrial design, Physical Sciences Reviews, 5(6), 2020, 517-519. https://doi.org/10.1515/psr-2019-0038

[17] Wang, M.: Applying Internet information technology combined with deep learning to tourism collaborative recommendation system, PLoS One, 15(12), 2020, e0240656. https://doi.org/10.1371/journal.pone.0240656

[18] Wang, X.: Personalized recommendation framework design for online tourism: know you better than yourself, Industrial Management & Data Systems, 120(11), 2020, 2067-2079. https://doi.org/10.1108/IMDS-05-2020-0278

[19] Yang, E.-K.; Lee, J.-H.: Understanding the design personalization of fashion products using computational design methods: practical insights into consumer perceptions, Fashion Practice, 15(3), 2023, 470-492. https://doi.org/10.1080/17569370.2022.2062139

[20] Yeh, C.-C.; Ku, E.-C.: Process innovation capability and subsequent collaborative team performance in travel planning: a knowledge exchange platform perspective, Current Issues in Tourism, 22(1), 2019, 107-126. https://doi.org/10.1080/13683500.2017.1328667