Personalized Recommendation and Interaction of Digital Media Based on Collaborative Filtering Algorithm

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Abstract. This article aims to explore the personalized recommendation and interaction methods of digital media based on CAD (Computer Aided Design) and RL (Reinforcement Learning). In this article, the related theories of CAD and RL are first deeply analyzed, and their potential application in personalized recommendation and interaction with digital media is discussed. Then, build a personalized recommendation model of digital media based on CAD and RL and realize accurate and personalized recommendation service by extracting the characteristics of digital media content, analyzing user behaviour data, and designing a reasonable RL algorithm. At the same time, this article also explores the optimization strategy of digital media interaction technology to improve the interactive experience between users and recommendation systems. The results show that the digital media recommendation and interaction method based on CAD and RL is significantly superior to the traditional methods in recommendation accuracy and user satisfaction. This method can capture users' interest preferences more accurately, provide personalized recommendations that are more in line with users' needs, and enhance users' experience through real-time interaction.

Keywords: Computer-Aided Design; Reinforcement Learning; Digital Media; Personalized Recommendation; Collaborative Filtering Algorithm
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1 INTRODUCTION

The rapid advancement of information technology has transformed digital media into the primary avenue for individuals to obtain information, entertainment, and leisure. With the rapid development of e-commerce, personalized product recommendations have become an important means to improve user experience and shopping conversion rates. In order to achieve more accurate and effective personalized recommendations, it is crucial to build an ontology semantic framework for user-oriented e-commerce personalized product recommendations. Deepak and Kasaraneni [1] discussed the importance, construction methods, and application prospects of this framework. Through the ontology semantic framework, it is possible to more accurately understand user needs and product attributes, thereby recommending products that better meet their needs. This can not only improve the accuracy of recommendations but also enhance the shopping experience for users. Semantic frameworks can construct personalized recommendation models based on user preferences, behaviours, and other information. This personalized recommendation method can meet the needs of different users and improve the targeting and effectiveness of recommendations. Reinforcement learning is a machine learning technique that learns how to achieve goals through trial and error. In reinforcement learning, agents learn and optimize their decision strategies through interaction with the environment to achieve the goal of maximizing cumulative rewards. When this technology is applied to personalized recommendations and interaction in digital media, agents can dynamically adjust recommendation and interaction strategies based on user feedback and behavioural data to provide content and services that are more in line with user preferences. In personalized recommendation of digital media, personalized reinforcement learning can help the system more accurately understand the interests and needs of users and adjust recommendation strategies in real-time. By analyzing user browsing history, purchasing behaviour, and other data, reinforcement learning algorithms can learn user preferences and decision-making processes and recommend content that better meets their needs based on this information. In addition, reinforcement learning can also be combined with other recommendation techniques, such as collaborative filtering and content recommendation, to improve the accuracy and efficiency of recommendations [2].

With the rapid development of network technology and the arrival of the big data era, personalized content recommendation has become a research hotspot in many fields. Guni et al. [3] focus on exploring how to use machine learning technology to personalize web-based user health interest content, to improve user efficiency and satisfaction in obtaining health information. Machine learning technology can establish user profiles by analyzing their historical behaviour and preferences and recommend personalized content to users based on these profiles. However, due to the massive and diverse nature of online information, users often find it difficult to find healthcare content that meets their interests and needs. Therefore, studying how to use machine learning technology to personally recommend health content is of great significance for improving the efficiency and quality of user access to health information. In digital advertising, the personalized recommendation visual communication design of digital media plays a crucial role. It not only affects the dissemination effect of advertising but also directly determines the user's perception and acceptance of advertising. Li [4] discussed the importance and implementation methods of personalized recommendation visual communication design for digital media in digital advertising. Personalized recommendation visual communication design can present advertising content that better suits the interests and needs of users. This targeted design approach can reduce user interference and aversion and improve the user experience. Through personalized recommendations and visual communication design, advertisements can more accurately reach the target audience, thereby increasing their exposure and click-through rates. This precise placement method can not only improve the effectiveness of advertising but also save advertisers advertising costs. Designers and advertisers need to focus on enhancing user experience and brand image while pursuing advertising effectiveness, ensuring the legality and morality of advertising. In light of the vast amount of digital media content available, the challenge lies in delivering precise and personalized recommendation services to users. This has become a focal point of contemporary research. CAD technology serves as a pivotal support for the creation of digital media content, while RL, a nascent machine learning paradigm, has demonstrated remarkable potential in the realm of recommendation systems. The aim of this study is to integrate CAD and RL, investigating personalized recommendation and interaction technologies within digital media. This integration aims to enhance the precision and user satisfaction of recommendation systems, carrying both significant theoretical value and practical implications.

With the advancement of technology and the increasing aesthetic needs of audiences, stage digital media design has become an indispensable part of modern performances. Liu and Chen [5] discussed a stage digital media design strategy based on fourth-order design. It aims to provide designers with a comprehensive and systematic design approach, ensuring that the visual effects of the performance are perfectly combined with artistic, technical, and ornamental elements. At the beginning of design, designers need to have a deep understanding of the project background, including the theme, style, purpose, etc., of the performance. After the design framework and concepts are determined, the designer needs to start refining the design plan. This includes selecting suitable projection equipment, material production, programming control, etc. At the same time, work closely with other teams, such as stage design and lighting, to ensure coordination and integration between digital media and other elements. At this stage, attention needs to be paid to details to ensure that every aspect of the design is perfectly presented. With the rapid development of the film industry and the strengthening of digital trends, movie recommendation systems have become a key technology to meet the personalized needs of users. Peng et al. [6] proposed a movie recommendation system framework that integrates deep reinforcement learning and personalized recommendation collaborative filtering, aiming to improve the accuracy of recommendations and user satisfaction. The movie recommendation system aims to recommend movies that meet the interests and preferences of users. Traditional recommendation methods, such as collaborative filtering, generate recommendations based on user historical behaviour and ratings. However, these methods may be limited by data sparsity and cold start issues. In recent years, the application of deep reinforcement learning in recommendation systems has gradually received attention, as it can optimize recommendation strategies by learning user behaviour and feedback. Using the initial recommendation list as input for deep reinforcement learning algorithms, learning user preferences and interests, and optimizing and adjusting the recommendation list. This can be achieved through methods such as deep Q-networks (DQN) and policy gradients. With the rapid development of the music industry and the growing demand for personalization, emotion-based music recommendation systems have become a hot research topic. Prisco et al. [7] proposed an emotion-based personalized music recommendation method induced by reinforcement learning. It aims to recommend suitable music to users based on their emotional state, thereby enhancing their music experience. There is a close connection between music and emotions, and people in different emotional states may have different music preferences. Traditional music recommendation methods are mainly based on the user's historical behaviour and preferences while ignoring the user's current emotional state. Therefore, it proposes to use reinforcement learning technology, combined with the emotional state of users, to achieve emotion-based personalized music recommendations. It uses reinforcement learning algorithms to learn how to recommend music based on the user's emotional state. The recommendation module can adjust the recommendation strategy based on user feedback (such as likes, comments, playback duration, etc.) to achieve better recommendation results.

Concurrently, CAD technology, supported by advancements in computer graphics and virtual reality, has expanded the diversity of digital media content creation. CAD not only streamlines production but also facilitates personalized customization. Despite these advancements, the integration of CAD and RL in personalized digital media recommendation and interaction remains underexplored. This study aims to bridge this gap, offering novel insights and methods for the development of a digital media recommendation system. Its contributions include providing innovative ideas and methods for personalized recommendation and interaction in digital media, with significant theoretical and practical implications. The primary innovations of this article are as follows:

(1) This article innovatively puts forward the method of combining personalized recommendation with real-time interaction. By designing an effective interaction mechanism, users can participate in the recommendation process more actively and further improve the user experience and satisfaction.

(2) This article constructs a feature representation model of digital media content by using CAD technology, which can effectively extract the semantic and visual features of media content. This feature representation method not only improves the accuracy of recommendations but also can better understand users' preferences and needs.

The article is organized into seven distinct sections. The introductory section outlines the research's background, significance, current status, content, methods, and overall structure. The second and third sections present an overview and analysis of CAD and RL's related theories, respectively. The fourth section delves into the construction of a personalized recommendation model for digital media, integrating CAD and RL principles. The fifth section delves into the optimization strategies for digital media interaction technology. The sixth section empirically verifies the effectiveness of the personalized recommendation model through simulation experiments. Finally, the concluding section summarizes the study's key contributions and limitations and offers insights into future research directions.

2 RELATED WORK

Personalized content recommendation has become one of its core competencies. The rise of data science and machine learning methods has provided strong technical support for personalized recommendations of social media content. Shahbazi and Byun [8] explored the combination of personalized recommendations of social media content with data science and machine learning methods. And how this combination can enhance user experience and drive the development of social media platforms. For users, finding information that interests them in a massive amount of content has become a challenge. The emergence of personalized recommendation technology can recommend content that best meets the needs of users based on their interests, behaviours, and other factors, thereby greatly improving the user experience. Collaborative filtering analyzes the historical behaviour of users and the behaviour of other users, identifies similar users or items, and recommends relevant content to users. Deep learning can automatically extract features from data, establish complex models, and further improve the accuracy of recommendations. Personalized recommendations are playing an increasingly important role in improving user experience and increasing user engagement. Taherdoost [9] explores how to use machine learning algorithms and neural networks to enhance personalized recommendations on social media platforms, aiming to provide more accurate and personalized content recommendations, thereby improving user satisfaction and platform activity. Traditional recommendation methods are mainly based on the user's historical behaviour and preferences, but this method is often limited by data sparsity and cold start issues. With the development of machine learning algorithms and neural networks, we can more effectively address these issues and improve the accuracy and personalization of recommendations. The collaborative filtering algorithm analyzes the user's historical behaviour and preferences, finds other users or content that are similar to the user's interests, and generates recommendations based on the behaviour of these similar users or the attributes of similar content. A large amount of user-generated content provides us with rich data resources to study and evaluate individual personality traits. Machine learning techniques, especially text mining methods, have played a crucial role in processing and analyzing these unstructured data. Tay et al. [10] explored how to use social media text mining for personality assessment and conducted an in-depth analysis of the effectiveness of personalized recommendations in this context. Personality assessment has always been a key area of research in psychology and social sciences. In recent years, with the development of machine learning and big data technology, more and more research has begun to focus on how to use social media data to evaluate individual personality traits. Social media text mining, as an effective data analysis method, can extract useful information from massive user-generated content, providing a foundation for personalized recommendations and other applications.

Vasudevan [11] creates a personalized information space that meets user needs, improving the efficiency and experience of user information reception. The emergence of this design approach has greatly changed the information dissemination mode of the traditional media era, making information more in line with the personalized needs of users. The role of design in shaping the context of digital media cannot be ignored. Meanwhile, this will also drive innovation and development in the digital media industry, bringing more possibilities for future information dissemination and social interaction. Firstly, design can influence the user's reception and understanding of information. An excellent personalized recommendation design can make users feel comfortable and convenient when browsing information, thus making them more willing to accept and understand the pushed content. Secondly, design can influence users' information consumption habits. By continuously optimizing recommendation algorithms and designing interfaces, users can be guided to form healthier and more rational information consumption habits. Finally, design can shape the brand image of digital media. Unique visual and interactive design can make digital media stand out among numerous platforms, forming a unique brand image. With the rapid development of edge computing and multicast technology, personalized recommendation has become more and more important in edge-assisted multicast systems. Wang et al. [12] explored how to use deep reinforcement learning technology to achieve personalized recommendations for edge-assisted crowdsourcing, aiming to improve the accuracy and efficiency of recommendation systems and provide users with a better experience. The combination of edge computing and multicast technology brings new opportunities for personalized recommendations. Edge computing can reduce data transmission delay and improve processing speed, while multicast technology can achieve rapid distribution and sharing of content. Deep reinforcement learning combines the advantages of both deep learning and reinforcement learning, enabling efficient decision-making and learning in complex environments. In personalized recommendation, deep reinforcement learning can learn from the user's historical behaviour and feedback, establish a user preference model, and generate personalized recommendation lists.

Personalized movie recommendation systems have become a key technology to meet users' viewing needs. Wang and Esquivel [13] proposed a personalized movie recommendation system based on Deep Deterministic Policy Gradient (DDPG). It aims to capture the personalized preferences of users and provide more accurate movie recommendations through reinforcement learning techniques. Traditional movie recommendation methods, such as collaborative filtering and content-based recommendation, mainly rely on the user's historical behaviour and preferences to generate recommendations. However, these methods often fail to handle the dynamic changes and long-term preferences of users effectively. In recent years, the application of reinforcement learning technology in recommendation systems has gradually received attention. Especially the Deep Deterministic Policy Gradient (DDPG) algorithm, which can handle large-scale and high-dimensional data and achieve effective policy learning in a continuous action space. Large online forums provide students with a platform for communication and learning. In order to help students learn more effectively, Wu et al. [14] explored the method of using supervised machine-learning techniques to predict academic performance in large online forums. By analyzing user behaviour, interaction data, and other related factors in the forum, a predictive model was established to provide personalized learning recommendations for students. During the model-building process, parameter tuning and model evaluation are also necessary. Parameter tuning aims to find the optimal combination of parameters for the model to improve prediction accuracy. Model evaluation evaluates the performance of a model through methods such as cross-validation, ensuring its stability and generalization ability. It explores methods for using supervised machine-learning techniques to predict learning outcomes in large online forums. By analyzing student behaviour data and other related factors, a predictive model was established to provide personalized learning recommendations for students. The experimental results indicate that the model has certain predictive performance and can provide useful references for students' learning.

The digital media teaching system has become an important component of modern education. In these systems, computer-aided design (CAD) technology for personalized recommendations is gradually emerging, providing new possibilities for teaching and learning. Xu [15] discussed the importance, application, and future development of computer-aided design for personalized recommendations in digital media teaching systems. In traditional teaching systems, students often can only learn according to a fixed course sequence and content, lacking a personalized learning experience. In digital media teaching systems, computer-aided design technology plays a crucial role. By utilizing advanced algorithms and models, CAD technology can achieve intelligent analysis and recommendation of learning resources. For example, by analyzing students' learning data and behaviour, CAD systems can predict their learning needs and interests and recommend relevant learning resources and courses for them based on this. With the popularization of Internet of Things technology and the rapid development of deep learning, how to use these advanced technologies to provide personalized recommendations of Western music history information for users has become a worthwhile research question. Yang [16] explored the potential and value of the Internet of Things and deep learning in recommending Western music history information and subsequently proposed a personalized recommendation system based on deep learning, which was verified to be effective through experiments. The Internet of Things technology can achieve a comprehensive collection of music history information and real-time tracking of user behaviour, providing a rich data foundation for personalized recommendations. Deep learning can extract users' potential interests and preferences from these big data, achieving accurate music history content recommendations. The combination of the two can not only improve the accuracy and efficiency of recommendation systems but also provide users with a more personalized and intelligent music history learning experience.

With the popularization of social media, a large amount of user-generated content provides us with rich data resources to study and evaluate individual personality traits. Machine learning techniques, especially text mining methods, have played a crucial role in processing and analyzing these unstructured data. Zhou et al. [17] explored how to use social media text mining for personality assessment and conducted an in-depth analysis of the effectiveness of personalized recommendations in this context. Personality assessment has always been a key area of research in psychology and social sciences. In recent years, with the development of machine learning and big data technology, more and more research has begun to focus on how to use social media data to evaluate individual personality traits. Social media text mining, as an effective data analysis method, can extract useful information from massive user-generated content, providing a foundation for personalized recommendations and other applications. In the field of digital media art and design, personalized recommendation is not only an optimization at the technical level but also a stage for creative thinking to be unleashed. Zhu [18] aims to explore how to stimulate and apply creative thinking in the personalized recommendation process in order to provide users with a more unique and artistic recommendation experience. Digital media art design combines technology and art, creating visually impactful and artistic works through creativity and conceptualization. The personalized recommendation is based on user behaviour and preferences, recommending content that meets their personalized needs. Integrating personalized recommendations into digital media art design can provide users with a more accurate and personalized art experience. Creative thinking refers to the ability to generate novel, unique, and valuable ideas and solutions during the thinking process. Creative thinking plays a crucial role in personalized recommendations. It can help designers explore the potential needs and interests of users from their perspective and recommend artworks that better meet their personalized needs.

3 RL THEORY AND ITS APPLICATION IN RECOMMENDATION SYSTEM

CAD, short for Computer-Aided Design, refers to the utilization of computer technology to aid designers in their work. This process digitizes all sorts of data, graphics, and information, enabling designers to carry out tasks more efficiently and precisely. CAD's evolution has spanned from basic two-dimensional drawings to intricate three-dimensional models, evolving from standalone design tools into comprehensive design systems. It has become an integral part of industrial design, architectural design, mechanical design, and numerous other fields. As computer technology continues to advance, CAD is also constantly evolving and improving. The enhanced capabilities of CAD software now allow designers to handle more significant and intricate design tasks. Furthermore, the integration of CAD with other technologies, such as virtual reality and artificial intelligence, has opened up new horizons and innovative possibilities for design work.

Digital media, on the other hand, refers to the medium that records, processes, disseminates, and acquires information in the form of binary numbers. This encompasses digital text, graphics, images, sounds, video footage, and animations. In the realm of digital media, CAD plays a pivotal role, as evident in Figure 1.

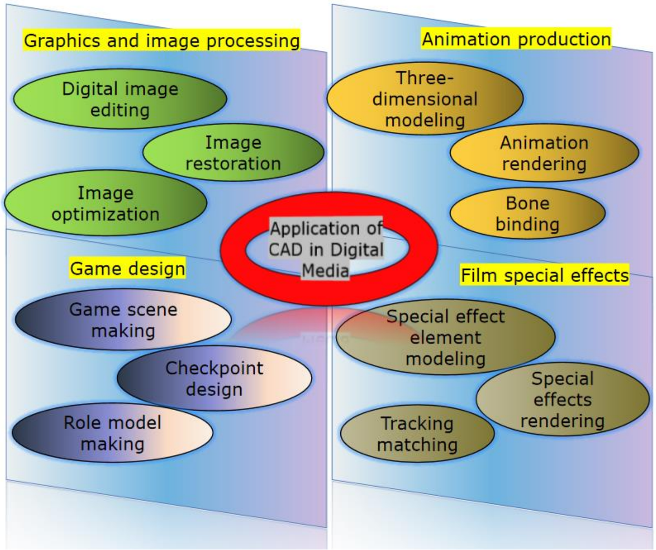

Figure 1: Application of CAD in digital media.

CAD technology covers many aspects, including 2D drawing technology, 3D modelling technology, parametric design technology and simulation analysis technology. These technologies have their own characteristics and advantages and can be selected and applied according to specific design requirements (see Table 1).

Technical classification	*Specific description*	*Main applications*	*Features and advantages*
Two-dimensional drawing technology	The basic technology of CAD is used to draw plane graphics and engineering drawings.	Architectural design, mechanical drawing, etc.	Rich drawing tools and editing functions to meet the drawing requirements of complex graphics.
Three-dimensional modelling technology	Key Technologies of Creating 3D Solid Models and Scenes	Product design, animation production, etc.	Powerful modelling functions and flexible editing tools realize the construction from simple geometry to complex organic models.
Parametric design technology	The design method is based on parameters and constraints that control the shape and size of design objects.	Mechanical design, industrial design, etc	Improve design flexibility and reusability, and reduce repetitive work and design errors.
Simulation analysis technology	The actual physical process is simulated by a computer to evaluate and optimize the design performance.	Engineering analysis, product design verification, etc.	Discover potential problems and defects in the design stage and improve the design quality and efficiency.

Table 1: Classification and characteristics of CAD technology.

RL is a branch of machine learning that studies how agents learn optimal strategies in interaction with the environment to maximize cumulative rewards. RL consists of three basic elements: status, action and reward. The agent chooses the action according to the current state, and the environment gives the new state and reward according to the action of the agent. The goal of the agent is to learn a strategy to maximize the cumulative reward from the initial state to the termination state. The basic principle of RL is to learn by trial and error. In the stage of continuous interaction with the environment, agents adjust their strategies according to the rewards they get in order to expect greater rewards in the future. RL algorithm usually includes two steps: value function estimation and strategy optimization. Value function estimation is used to evaluate the value of each action in the current state; Strategy optimization chooses the best action according to the result of the value function. The classification and comparison of RL algorithms are shown in Figure 2.

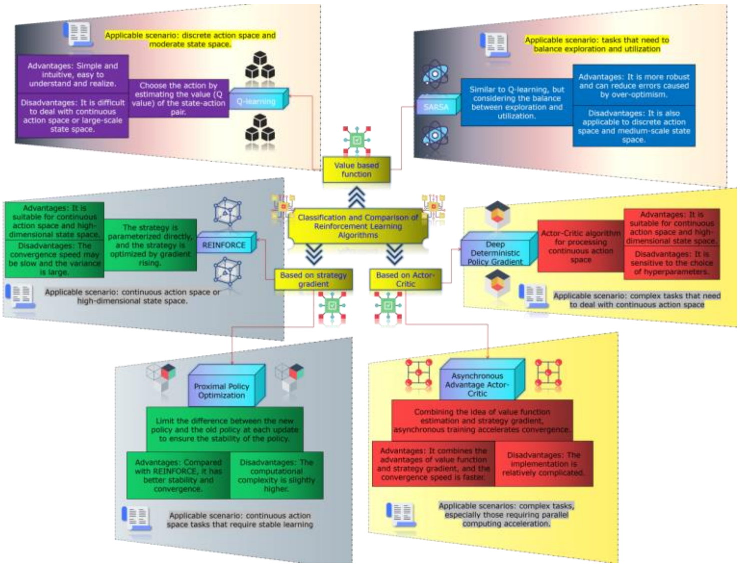

Figure 2: Classification and comparison of RL algorithms.

The utilization of RL in recommendation systems manifests primarily in two distinct aspects. Firstly, it optimizes the recommendation strategy by employing RL algorithms, thereby enhancing recommendation accuracy and user satisfaction. Secondly, RL is employed to tackle the dynamic and real-time challenges encountered within the recommendation system. Table 2 shows the challenges and opportunities of RL in digital media recommendation.

Challenge item	*Simplified description*	*Opportunity term*	*Simplified description*
Content diversity and complexity	How do we effectively extract and integrate the characteristics of various digital media contents?	Combined with deep learning	Use deep learning to improve the effect of feature extraction and provide more accurate recommendations.
Large-scale users and data processing	How do you design an efficient and scalable RL algorithm to deal with a large number of users and data?	Using user feedback to optimize strategy	Dynamic adjustment and optimization of recommendation strategy by using user feedback data
Privacy and security issues	How do you ensure privacy and security	Combine with other technologies	Combine natural language processing, computer vision and

	when handling user data?	to provide intelligent services.	other technologies to provide intelligent and personalized recommendations.

Table 2: Challenges and opportunities.

4 PERSONALIZED RECOMMENDATION MODEL OF DIGITAL MEDIA BASED ON CAD AND RL

4.1 Personalized Recommendation System

A personalized recommendation system is a tool that tailors its suggestions to individuals based on their interests, preferences, and behaviours. By delving into user data, it uncovers latent needs and interests, filters through vast amounts of content to identify potentially appealing items, and then presents these to users in the form of recommendation lists, tags, and other formats.

Depending on the recommendation algorithms and scenarios, personalized recommendation systems can be categorized as follows: (1) Content-Based Recommendation Systems: These systems primarily rely on users' historical behaviour data and item content attributes to make suggestions. By analyzing the attributes of items users prefer, they identify similar items aligned with users' interests and recommend them. This method is particularly effective for recommending multimedia content such as text, images, and videos. (2) Collaborative Filtering (CF) Recommendation Systems: These systems primarily use user behaviour data along with data from other users to make recommendations. By analyzing a user's behaviour and comparing it to similar users, they discover items that may interest the user and recommend them. This method is ideal for scenarios with extensive user behaviour data and strong item correlations. (3) Hybrid Recommendation Systems: These systems combine various recommendation methods, such as content-based and CF, to enhance recommendation accuracy and satisfaction. Hybrid systems can flexibly select and combine appropriate recommendation algorithms and technologies based on specific application scenarios and requirements. The recommended system flow is depicted in Figure 3.

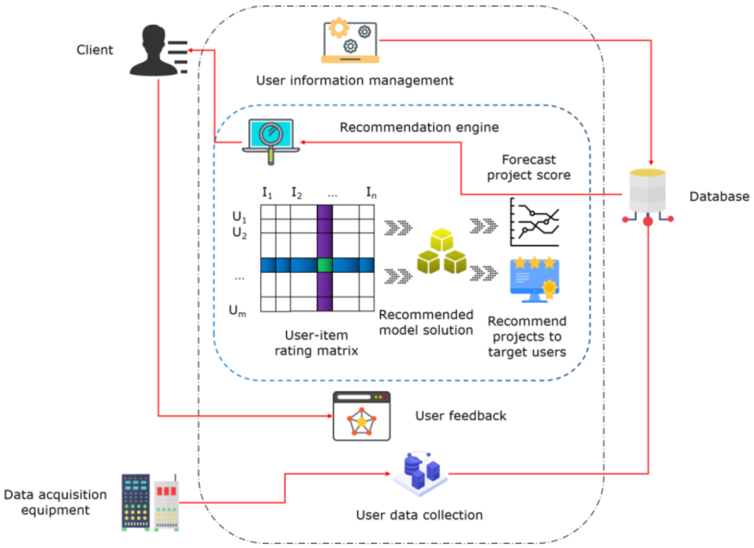

Figure 3: Recommended system flow chart.

The personalized recommendation algorithm lies at the heart of realizing a personalized recommendation system. Presently, the most commonly utilized algorithms encompass those based on association rules, matrix decomposition, and deep learning. Firstly, the association rule-based recommendation algorithm identifies combinations of items that may interest users by mining associations between them. This method is particularly effective for scenarios such as shopping cart analysis and bundling. Secondly, the matrix decomposition-based recommendation algorithm employs machine learning techniques to decompose the user-item rating matrix, revealing hidden feature vectors for both users and items. This is well-suited for tasks like rating prediction and Top-N recommendations. Lastly, with the ever-evolving deep learning technology, an increasing number of studies are applying it to recommendation systems. The deep learning recommendation algorithm enhances recommendation accuracy and personalization by learning intricate user behaviour patterns and the underlying characteristics of items. In the recommendation system, the user i 's evaluation of an item j is defined as follows:

$$r_{ij} = \begin{cases} r_{ij} & \mathit{If\ i\ scores\ item\ j} \\ 0 & \mathit{If\ i\ doesn't\ grade\ item\ w} \end{cases} \tag{1}$$

Calculating the cosine similarity of vector a and vector b is to calculate the included angle θ of these two vectors. Assume that the coordinates of vector a and vector b are:

$$a_1, b_1 \qquad a_2, b_2 \tag{2}$$

Then:

$$\cos\theta = \frac{a \cdot b}{\|a\|\|b\|} = \frac{a_1 b_2 + a_1 b_2}{\sqrt{a_1^{\ 2} b_1^{\ 2}} \times \sqrt{a_2^{\ 2} b_2^{\ 2}}} \tag{3}$$

On this basis, it is extended to a multi-dimensional space and let a and b be two n-dimensional vectors, where:

$$a = \ a_1, a_2, a_3, \ldots, a_n \tag{4}$$

$$b = \ b_1, b_2, b_3, \ldots, b_n \tag{5}$$

Then the cosine of the included angle θ between a and b is equal to:

$$\cos\theta = \frac{\sum_1^n a_i \cdot b_i}{\sqrt{\sum_1^n a_i^2} \times \sqrt{\sum_1^n b_i^2}} \tag{6}$$

User portrait is an important concept in personalized recommendation systems, which refers to the abstract representation of users' interests, preferences and behaviours. Constructing an accurate user portrait is one of the key steps to realizing personalized recommendations. The process of user portrait construction includes data collection, feature extraction and model training. First, it is necessary to collect user behaviour data, social data, content consumption data, etc., from multiple data sources. Then, the collected data are processed and transformed by feature engineering technology to extract features that can reflect users' interests. Finally, the machine learning algorithm is used to train and learn the extracted features, and the user portrait model is obtained. In order to maintain the accuracy and timeliness of user portraits, it is necessary to formulate appropriate update strategies. On the one hand, new user data can be collected regularly and updated in the user portrait model. On the other hand, online learning technology can be used to update and adjust users' portraits in real time to adapt to the changes in users' interests and the needs of recommendation systems.

4.2 Overall Framework Design of the Model

When building a personalized recommendation model of digital media based on CAD and RL, it is necessary to design a comprehensive and efficient overall architecture at first. The architecture should include the following core components:

(1) Data preprocessing layer: This layer is responsible for collecting, cleaning, and integrating digital media data from different sources, including user behaviour data and media content data. This layer processes the raw data into a format suitable for subsequent analysis and machine learning algorithms.

(2) Feature extraction layer: Using CAD technology, key features, such as visual features such as colour, shape and texture, as well as deep-seated features such as semantics and emotion, are extracted from digital media content. These features will be used as the input of the recommendation model. In the feature extraction layer, this article uses CAD technology to deal with digital media content. Firstly, the visual features of the image are extracted by an image processing algorithm, such as colour histogram, edge detection, texture analysis and so on. Then, natural language processing technology is used to analyze the semantic and emotional content of the text, and information such as keywords, themes and emotional tendencies is extracted. These extracted features will be transformed into numerical vectors or embedded representations for input into subsequent machine-learning models.

(3) RL layer: In this layer, the RL algorithm is implemented to learn users' personalized preferences and dynamic behaviour patterns. RL agent constantly optimizes the recommendation strategy by interacting with the environment (i.e., the recommendation system). The cosine similarity calculation formula adopted in this article is as follows:

$$sim\ a,b\ = \frac{num\ a,b}{\sqrt{num\ a}\sqrt{num\ b}} \tag{7}$$

$sim\ a,b$ represents the similarity between items a and b, $num\ a,b$ represents the number of intersection elements of the attribute category matrix of items a and b, and $num\ a$ and $num\ b$ represent the number of non-zero components of the attribute vector of items a and b respectively. In this article, the modified cosine similarity is used to calculate:

$$sim\ u,v\ = \frac{\sum_{i\in I_{u,v}} R_{u,i}-\bar{R}_u\ \ R_{v,i}-\bar{R}_v}{\sqrt{\sum_{i\in I_u} R_{u,i}-\bar{R}_u\ ^2}\sqrt{\sum_{i\in I_v} R_{u,i}-\bar{R}_v\ ^2}} \tag{8}$$

Vector $\vec{u}$ and vector $\vec{v}$ represent the scores of users u and v in n dimension project space; I_{uv} represents the set of items scored jointly by users u and v; I_u and I_v represent the item sets scored by users u and v respectively; $R_{u,i}$ and $R_{v,i}$ represent the ratings of users u and v on the item i, respectively; $\bar{R}_u$ and $\bar{R}_v$ represent the average scores of users u and v respectively. At the same time, Benvenga takes $r_{\min}$ as a factor to adjust and improve to accurately reflect the similarity between the two optimizations:

$$sim\ u,v\ = \frac{r_{\min}}{2}\times\frac{\left|I_{uv}\right|}{\sum_{i\in I_{uv}\omega_P}\left|r_{u,v}-r_{v,i}+\frac{r_{\min}}{2}\right|} \tag{9}$$

ω_P represents the influence weight of the user's scoring criteria, I_{uv} represents the item set evaluated by two users together, and $r_{\min}$ represents the value difference of the scoring range.

(4) Recommendation generation layer: According to the strategy learned by the RL agent, combined with the user portrait and current context information, a personalized digital media recommendation list is generated.

(5) Evaluation and feedback layer: Responsible for evaluating the recommendation effect, collecting feedback data from users, and feeding this information back to the RL layer for continuous optimization and updating of the model.

4.3 Implementation and Optimization of RL Algorithm in Digital Media Recommendation

In the RL layer, this article chooses the appropriate RL algorithm to realize personalized recommendations. Specifically, the status can be defined as the user's historical behaviour and current context information, the action is the recommended digital media content, and the reward is the user's feedback on the recommended content (such as click, viewing time, etc.). Then, the RL agent is trained to learn the optimal recommendation strategy.

In order to realize and optimize the RL algorithm, the following strategies are adopted: (1) Using a deep neural network to approximate value function or strategy function to deal with high-dimensional state space and action space; Using experience playback technology to stabilize the learning process and improve the sample efficiency; By exploring and using balance technology, we can strike a balance between exploring new user interests and using known user preferences.

In the stage of model training and optimization, the following strategies are adopted to improve the performance of the recommendation model: pre-training with large-scale data sets to learn common user interests and behaviour patterns; fine-tuning the data set in a specific field to meet the needs of specific scenarios and user groups; Online learning technology is used to update the model parameters in real-time to adapt to the changes of users' interests and the needs of recommendation systems.

5 DIGITAL MEDIA INTERACTION TECHNOLOGY

In a personalized recommendation system, interactive technology plays a vital role. By introducing interactive technology, the recommendation system can capture users' interests and needs more accurately, thus providing more personalized recommendation content. Specifically, this article applies the following aspects of interactive technology to personalized recommendations:

(1) User input mode: Through the touch screen, voice recognition and other technologies, users can provide their own preferences and demand information to the recommendation system more conveniently. This information can be used as the input of a recommendation algorithm to generate a recommendation list that is more in line with users' needs.

(2) Real-time feedback mechanism: The recommendation system can obtain users' feedback on the recommended content in real-time through interactive technology, such as clicking, rating and commenting. This feedback information can be used to update the user portrait and optimize the recommendation algorithm, making the recommendation results more accurate and personalized.

(3) Interactive recommendation interface: By designing an interactive recommendation interface, the recommendation system can guide users to explore and discover more deeply. For example, visualization technology can be used to show the relevance and hierarchical structure of recommendation results, which can help users better understand the recommended content and discover new points of interest.

To enhance the precision of personalized recommendations and boost user satisfaction, this article implements an interactive optimization approach that relies on user feedback, as demonstrated in Table 3.

Interactive optimization strategy	Detailed description
Collect and analyze user	By collecting users' feedback information such as clicks, ratings and

feedback data.	comments on the recommended content and using data analysis technology to mine and analyze this information, we can understand users' satisfaction and dissatisfaction with the recommended results and find out the existing problems and improvement directions in the recommendation system.
Optimize recommendation algorithm and model.	According to the results of the analysis of user feedback data, the recommendation algorithm and model are optimized to improve the accuracy of personalized recommendations.
Design an interactive learning mechanism.	An interactive learning mechanism is designed to allow the recommendation system to dynamically adjust the recommendation strategy according to the real-time feedback of users and gradually adapt to the individual needs of users in the process of continuous learning to continuously improve the performance of the recommendation system and user satisfaction.

Table 3: Optimization strategy.

In order to evaluate the effect of digital media interaction technology on personalized recommendations and make an in-depth analysis, this article collects users' evaluation information on the overall satisfaction, ease of use and accuracy of the recommendation system through questionnaires and interviews. This information can directly reflect the user's acceptance and experience of the recommendation system. The result is shown in Figure 4.

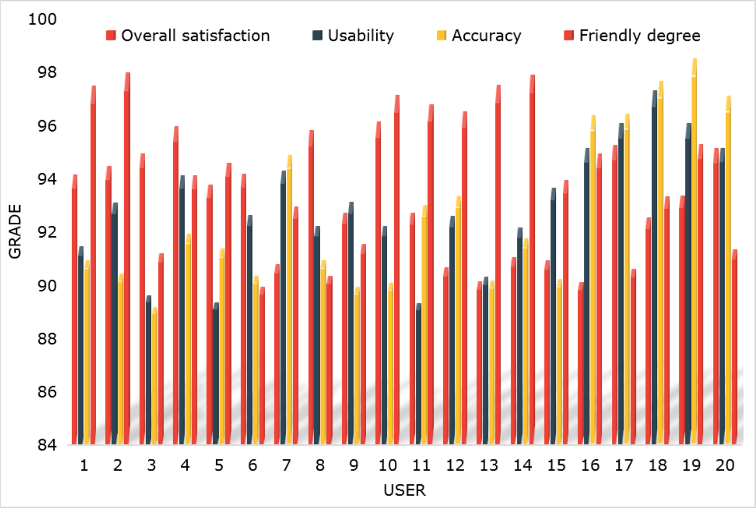

Figure 4: User feedback results.

6 SIMULATION EXPERIMENT DESIGN AND RESULT ANALYSIS

The experimental environment in this section is built on a high-performance computing platform, and the necessary software and hardware resources are configured to support large-scale data processing and machine learning algorithm training. The experiment uses several digital media data sets in real scenes, which cover images, texts, videos and other media types and contain rich user behaviour information. In the construction of an experimental environment, this article pays attention to repeatability and expansibility. All experimental codes are written in Python and other mainstream programming languages and are realized by relying on the open-source machine learning framework. At the same time, the experiment recorded the experimental configuration and parameter settings in detail to ensure that other researchers can reproduce our experimental results. To assess the effectiveness of the personalized recommendation system, it's crucial to select appropriate evaluation metrics and techniques for quantitative analysis. This article utilizes indicators such as recall rate, F1 value, AUC value, and recommendation accuracy. During the experimental design phase, the study defines its objectives, comparison methodologies, and evaluation metrics. Objectives include validating the model's recommendation accuracy, real-time performance, and interpretability.

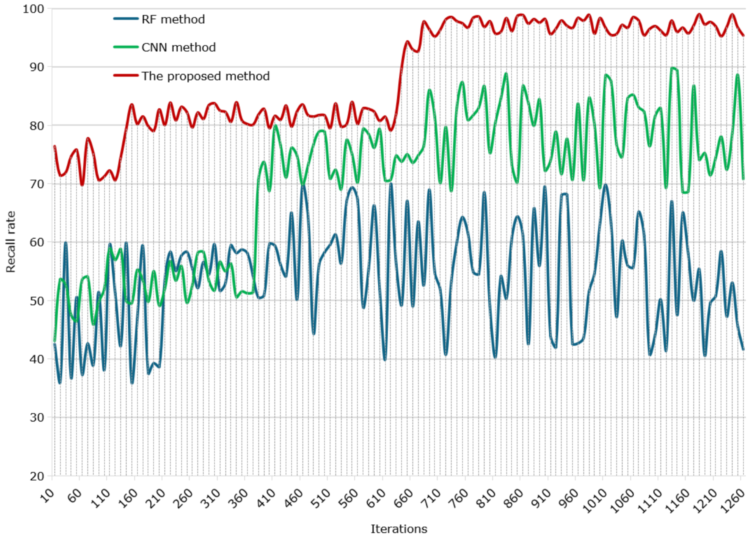

Figure 5: Recall rate.

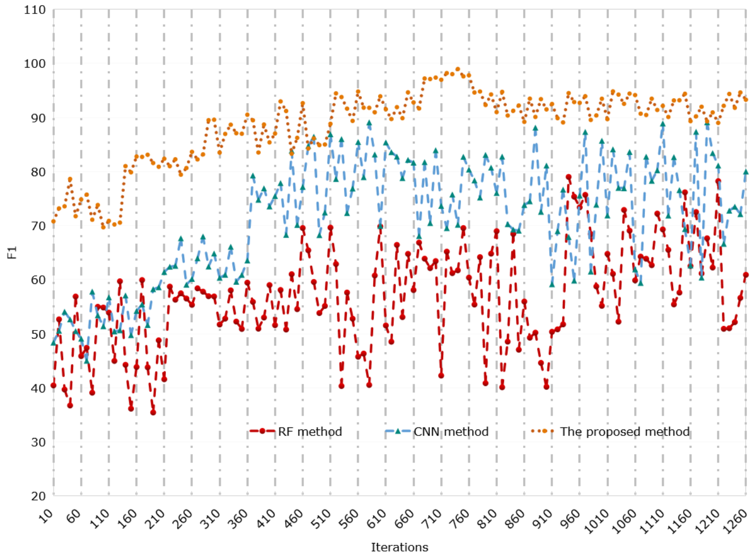

Figure 6: F1 value.

To comprehensively evaluate the model's performance, several representative benchmark methods are chosen as comparison baselines. The implementation process involves conducting experiments step-by-step according to the predefined plan. Initially, the proposed model is trained and fine-tuned to optimize its performance on the training set. Subsequently, a preliminary evaluation is conducted on the validation set, leading to adjustments based on the evaluation outcomes. Finally, a comprehensive evaluation is performed on the test set, comparing the model against the benchmark methods. The recall rate results are depicted in Figure 5.The experimental result of the F1 value is shown in Figure 6. The AUC value situation is shown in Figure 7. The recommendation accuracy is shown in Figure 8.

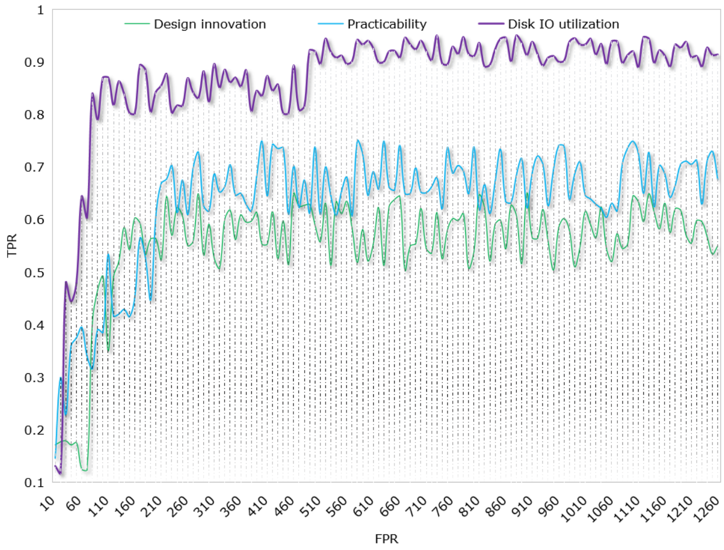

Figure 7: AUC value.

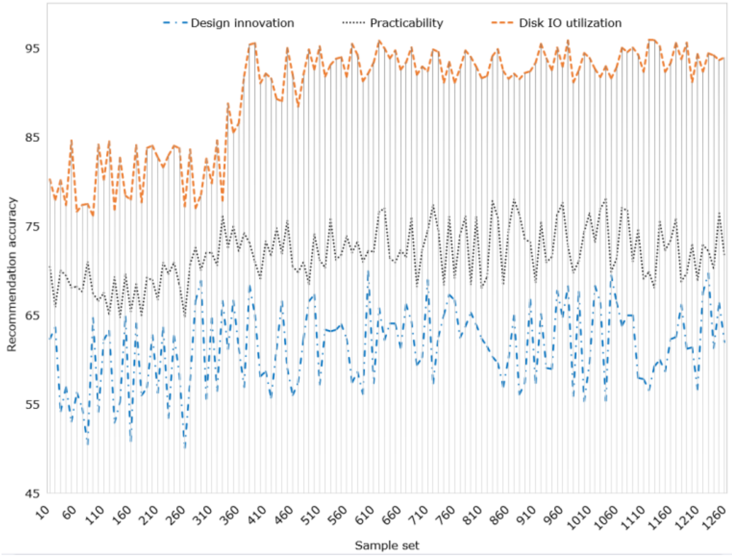

Figure 8: Recommendation accuracy.

In terms of comparative analysis, this section thoroughly examines the strengths and weaknesses of the proposed model alongside the benchmark method across various dimensions. The results reveal that the proposed model boasts substantial advantages in recommendation accuracy, maintaining both high real-time performance and interpretability. Drawing upon the experimental findings and comparative analysis, the following conclusions are reached: firstly, the proposed personalized recommendation model holds promise for widespread application within the realm of digital media. Secondly, the model surpasses the benchmark method in terms of recommendation accuracy, real-time performance, and interpretability. Lastly, the experimental outcomes also offer valuable insights and guidance for further model optimization and algorithm improvement.

7 CONCLUSIONS

This study centers on a personalized recommendation model tailored for digital media, leveraging CAD and RL technologies. Through meticulous model development, simulation experiment design and implementation, and rigorous analysis of experimental outcomes, we have achieved meaningful research advancements.

In terms of model development, we have successfully integrated CAD technology with RL algorithms, introducing a novel personalized recommendation model. This model is adept at extracting key features from digital media content, offering intelligent recommendations tailored to users' unique preferences and dynamic behavioural patterns. By embedding RL algorithms, the model continuously learns from user feedback, optimizing recommendation strategies to provide more precise and personalized services.

For the simulation experiment, we have established a comprehensive experimental framework, utilizing real-world digital media datasets for rigorous verification. When compared to benchmark methods, our model demonstrates significant advantages in recommendation accuracy, real-time performance, and interpretability. These findings strongly support the model's effectiveness.

Our contributions extend beyond enriching the personalized recommendation research domain; they offer fresh perspectives and methodologies for the digital media industry. Specifically, our research outcomes aim to enhance user experience and service quality on digital media platforms, fostering innovation and industry growth. Furthermore, our research methods and technical approaches provide valuable insights for other related fields. Looking ahead, we remain committed to a spirit of continuous learning and exploration, striving to push the boundaries of personalized recommendation technology.

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