International Journal for Housing Science and Its Applications
Publish August 10, 2025. Volume 46, Issue 4 Pages 2076-2086

https://doi.org/10.70517/ijhsa464178

Innovation and Practice of Socialized Development Models for Winter Sports in Higher Education Institutions in Heilongjiang Province Driven by Resource Advantages

Mingming Zhang[1,*], Dachun Zhang[1] and Leilei Zhang[2]
[1] HeiHe University, Physical Education Institute, Heihe, Heilongjiang, 164300, China
[2] Department of Physical Education, QingDao City University, Qingdao, Shandong, 266000, China
Corresponding authors: (e-mail: zmm810408@163.com).

Abstract This study addresses the demand for socialized sharing of ice and snow sports resources in higher education institutions in Heilongjiang Province, proposing a “dual-core driven” development model. It constructs an intelligent resource integration platform based on the k-nearest neighbor clustering algorithm and optimizes teacher participation mechanisms using an agency incentive model. Through simulation experiments, the method is validated to significantly enhance resource sharing efficiency. The k-nearest neighbor clustering algorithm achieves 99.74% accuracy and 98.98% recall rate (converging after 30 iterations), representing a 6-percentage-point improvement over traditional methods. Under 500 concurrent users, resource sharing speed reaches 583.94 MB/s, with a peak throughput of 760.05 MB/s, marking a 31.7% improvement over cloud computing solutions. The sports resource information integration system constructed in this paper demonstrates strong transmission stability, with a resource loss rate of only 3.6% under high-concurrency scenarios (1,000 users), which is 1.4-2.6 percentage points lower than the comparison method. Case analysis shows that resource integration efficiency reaches 99.17%, with an average efficiency exceeding 98% across the five major resource categories. Empirical evidence indicates that this model effectively addresses the challenges of scattered, low-quality, and stagnant winter sports resources through technological innovation and mechanism coordination, providing a scalable path for the socialized development of winter sports in cold-region universities.

Index Terms Neighborhood Propagation Clustering Algorithm, Resource Sharing Incentives, Principal-Agent Model, Winter Sports Resources, Resource Integration, Socialized Development

I. Introduction

In recent years, with the continuous development of winter sports in China, winter sports education and teaching have increasingly gained attention in higher education institutions [1], [2]. Heilongjiang Province is a key base for winter sports in China, boasting unique winter sports education resources within its universities, as well as benefiting from the rapid development of winter tourism and the winter sports industry [3]-[5]. However, in the new era, traditional university winter sports education models no longer meet the needs of societal development. How to promote the socialization of university winter sports education has become a focal point of educational reform and development in Heilongjiang Province [6]-[9].

Heilongjiang Province is home to renowned universities such as Heilongjiang University of Science and Technology, Harbin Engineering University, Northeast Forestry University, and Heilongjiang University, which possess abundant teaching resources in winter sports education [10]-[12]. Currently, the main content of winter sports education in Heilongjiang Province's universities includes speed skating, short-track speed skating, ice hockey, cross-country skiing, snowboarding, and other winter sports [13]-[15]. However, due to issues such as the small scale of university winter sports education, a lack of specialized talent, and insufficient socialized educational resources, university winter sports education often fails to meet students' needs [16]-[18]. The socialized development of winter sports requires universities in Heilongjiang Province to strengthen cooperation with industry associations and enterprises, establish a team of winter sports instructors, expand off-campus winter sports teaching resources, and organize winter sports events and competitions to promote the socialized development of winter sports education in universities, improve teaching standards and quality, and contribute to the development of winter sports in China [19]-[21].

The core idea of this article is to achieve optimal resource allocation and efficiency improvement through a systematic approach. First, it proposes a development path for the socialization of university sports services and identifies the need to establish a regional university ice and snow sports resource-sharing platform. Based on the concept of collaborative sharing, through government coordination, it integrates ice and snow sports venues, facilities, courses, and faculty resources from universities and social organizations within the region to establish a digital and intelligent sharing platform and establish clear sharing rules. This includes supporting cross-campus course selection and jointly organizing events, forming a hub for resource aggregation and flow. Second, in response to the massive and diverse winter sports resource data aggregated by the platform, the neighbor propagation clustering algorithm is introduced for intelligent processing of resource data. This algorithm can automatically determine the number of clusters, handle complex data types, and has good real-time performance and interpretability. By calculating the similarity between resource points, iteratively updating membership and availability, and ultimately accurately identifying cluster centers and allocating samples, the algorithm achieves intelligent classification and organization of winter sports course resources, venue information, competition data, etc., thereby enhancing user search efficiency and platform management intelligence. Based on this, a sports resource sharing incentive model grounded in agency theory is established. In this model, the platform is regarded as the principal, and teachers as agents. Considering factors such as teacher effort, platform service investment, psychological incentive effects, and resource utilization rates, a mathematical model is constructed that includes platform revenue functions, teacher revenue functions, participation constraints, and incentive compatibility constraints. The aim is to design optimal revenue distribution ratios and reward/punishment mechanisms to maximize teachers' enthusiasm for participating in ice and snow sports resource sharing by satisfying their multi-level needs, especially psychological revenue perceptions, thereby forming a positive synergy between the platform and teachers.

II. Innovative Pathways for the Integration of Higher Education Sports Resource Information and Social Development

II. A. Development Pathways for Socialized Services in Higher Education Physical Education

Based on the principles of collaborative sharing and the trends in educational informatization, a regional sports resource sharing model among universities will be established through the coordination of government authorities, aiming to achieve the digitization, platformization, and intelligentization of sports resources among universities within the region. Specifically, first, through the coordination of educational authorities, an open regional university sports resource sharing platform will be constructed to centrally integrate sports resources from universities and social sports organizations, and clear rules for resource sharing will be established, covering aspects such as resource uploading, access permissions, and copyright protection. Regional universities, education departments, sports associations, and other entities will be invited to join as member units and participate in platform development. Second, universities within the region can collaborate to offer online sports courses, allowing students to enroll in courses across institutions. The shared platform will coordinate sports events to optimize resource allocation. Additionally, a dynamic update mechanism will be implemented to ensure the timeliness and practicality of shared resources, with regular inspections and evaluations to facilitate resource iteration and updates.

II. B. Clustering of Digital Sports Resource Data

The massive and diverse ice and snow sports resource data aggregated by the platform urgently requires scientific and effective organization and management methods to fully leverage its value, improve user search efficiency, and enhance the platform's intelligent service capabilities. To this end, this section introduces the k-nearest neighbor clustering algorithm for data processing.

II. B. 1) Advantages of the nearest neighbor clustering algorithm

The k-nearest neighbor clustering algorithm is a clustering algorithm based on a graph model. This algorithm determines clustering results by calculating the similarity between data points and information propagation. Unlike traditional clustering algorithms, the k-nearest neighbor clustering algorithm does not require the number of clusters to be predefined, but instead automatically selects representative samples as cluster centers. The k-nearest neighbor clustering algorithm is feasible for clustering digital sports resource data. It can help universities or other institutions perform effective clustering analysis on digital sports resource data, discover potential associations and patterns, and thereby support better resource management and utilization. The reasons why the k-nearest neighbor clustering algorithm is feasible for clustering digital sports resource data are as follows:

(1) Automatic determination of the number of clusters: The algorithm can automatically determine the appropriate number of clusters based on the characteristics of the data itself, without the need for prior specification.

(2) Consideration of similarity between data points: By calculating the similarity between data points, the algorithm can group similar data points together to form meaningful clusters.

(3) Adaptability to diverse data types: The k-nearest neighbor clustering algorithm is applicable to various types of data, including digital sports resource data. It can process data with different dimensions and feature types to form corresponding clusters.

(4) Good interpretability: The final clustering results are obtained using samples with high membership scores as representative samples, making the clustering results easier to understand and interpret.

(5) Good real-time performance: The iterative process of the k-nearest neighbor clustering algorithm is fast, enabling it to process large-scale datasets in a short time.

II. B. 2) Steps for clustering digital sports resource data

The steps for processing digital sports resource data using the k-nearest neighbor clustering algorithm are as follows:

Step 1: Calculate the similarity between all data point pairs and initialize the availability $a(i,k)$ and affiliation $r(i,k)$ of each data point.

In the k-nearest neighbor clustering algorithm, calculating the similarity between data point pairs is a key step. The similarity between two data points can usually be calculated using the following formula:

$$S(i,j) = -d(i,j) \tag{1}$$

In the formula, $d(i,j)$ represents the distance between data point i and data point j and is mainly calculated using the following formula:

$$d(i,j) = \left(\sum\left(\left|x_i - x_j\right|^p\right)\right)^{\frac{1}{p}} \tag{2}$$

In the formula, x_i and x_j represent the feature values between data point i and data point j respectively, and p is a parameter.

Step 2: In each iteration, update the values of availability and belongingness based on the similarity between data points and the current availability and belongingness. The iterative calculation formulas for the availability of each data point are as follows:

$$a(i,k) = (1-\lambda) * a(i,k) + \lambda * \max\left\{r(j,k) + s(j,j') \mid i \neq j, j \neq k\right\} \tag{3}$$

In the formula, $r(j,k)$ represents the membership degree between data point j and candidate cluster center k, $s(j,j')$ represents the similarity or negative distance between data point j and data point j', and λ represents a damping coefficient.

The iterative formulas for calculating the membership degree of each data point are as follows:

$$\begin{aligned} r(i,k) = (1-\lambda) * r(i,k) + \lambda * (s(i,k) \\ - \max\left\{a(j',k) + s(j',k) \mid j' \neq i, j' \neq k\right\}) \end{aligned} \tag{4}$$

In the formula, $s(i,k)$ represents the negative distance between data point i and candidate cluster center k, $a(j',k)$ represents the availability between data point j' and candidate cluster center k, $s(j',k)$ denotes the propagated updated accessibility between data point j' and candidate cluster center k respectively.

Step 3: Select the data point with the highest membership degree as the cluster center based on the values of accessibility and membership degree. The formula for selecting the cluster center is as follows:

$$k' = \arg\max\left\{a(i,k) + r(i,k)\right\} \tag{5}$$

Step 4: Assign samples: Assign each data point to the cluster center most relevant to it. The calculation formula for this process is as follows:

$$y(i) = \arg\max\left\{s(i,k') + a(i,k')\right\} \tag{6}$$

In the formula, $s(i,k')$ represents the similarity or negative distance between data point i and cluster center k', and $a(i,k')$ represents the availability between data point i and cluster center k'.

Step 5: Iteration termination: When the change in the cluster center is less than the given threshold, stop the iteration. The formula for calculating the change in the cluster center is as follows:

$$d_c = \frac{\|k_{new} - k_{all}\|}{N} \tag{7}$$

In the formula, k_{new} and k_{all} represent the sets of all cluster centers obtained in the current iteration and the previous iteration, respectively, and N represents the number of cluster centers.

If d_c is less than the given threshold, the iteration stops; otherwise, the iteration continues. The final clustering result of the digitized sports resource data consists of the cluster centers and the data points assigned to them.

II. C.Sports Resource Sharing Incentive Model

The richness and vitality of platform resources ultimately depend on the sustained commitment and willingness to share of resource providers—particularly teachers. The maximum effectiveness of a technical platform must be built on the foundation of fully mobilizing human initiative. Therefore, how to design effective incentive mechanisms to motivate university teachers to actively and high-quality participate in resource sharing has become a critical component in ensuring the sustainable development of the entire model. This section aims to establish an incentive model and formulate incentive mechanisms that can motivate teachers to participate in resource sharing, tailored to meet the needs of teachers.

Based on the relationship among students, teachers, and the platform, students act as resource consumers and pay fees to the platform. The platform then compensates teachers based on resource usage. Teachers who utilize resources must also pay fees. The platform must reach a revenue-sharing agreement with teachers. Therefore, mapping this relationship to an agency model, it should be described as: the platform acts as the “principal,” and teachers act as the “agents.” Teachers create resources through their efforts, but the platform cannot observe the teachers' efforts; the only information it can observe is the number of resource accesses. Resource access volume is somewhat related to effort, depending on resource usage. Thus, teachers' efforts and resource access volume constitute incomplete information about resource users' actions. The platform's challenge is how to compensate teachers based on this observed information, adequately meet their material needs, and enhance their enthusiasm for participating in resource sharing.

II. C. 1) Model Assumptions and Symbol Definitions

(1) Assume that teachers' work efforts are divided into material incentives and spiritual incentives, which are a_m and a_s, respectively, and that a_m and a_s are independent of each other. The final return on resources is a function of the combined effects of the two types of effort, which is set as a Douglas function:

$$y = f(a_m, a_s) + \theta = a_m^{\alpha} a_s^{1-\alpha} + \theta \tag{8}$$

Among these, $\theta \sim N(0,\sigma^2)$ represents a random variable, symbolizing exogenous uncertainty factors. $\alpha(0 < \alpha < 1)$ indicates the importance of material incentives, $1-\alpha$ indicates the importance of spiritual incentives, $\alpha > 0.5$ indicates that the importance of material incentives is greater than that of spiritual incentives, otherwise the importance of material incentives is less than that of spiritual incentives. Assuming that the cost of teacher effort $c(a)$ is equivalent to monetary cost, for simplicity, let the cost of material incentive effort and spiritual incentive effort be $C = \frac{1}{2} b(a_m^2 + a_s^2)$. $b > 0$ represents the cost coefficient, and the larger b is, the greater the negative utility brought by the same effort.

(2) Assume that the platform's expenditures consist of two parts. The first part is the platform service investment of S, with the maximum possible investment being S_m; the second part is the benefits provided by the platform to teachers. Assume that the benefit distribution coefficient for teachers is $\beta(0 \le \beta \le 1)$.

(3) Assume that teachers pursue higher-level needs such as a sense of achievement and growth, and that platform services have an incentive effect on teachers, causing them to perceive their benefits as greater than the actual benefits. This is reflected by the psychological incentive effect coefficient η_1. η_1 is related to service intensity $S / S_m (0 \le S / S_m \le 1)$, platform efficiency $\rho_1 (0 \le \rho_1 \le 1)$, and teacher psychological sensitivity coefficient $\mu_1 (0 \le \mu_1 \le 1)$, set as $\eta_1 = \rho_1 \mu_1 S / S_m$.

(4) Assume that the platform's revenue consists of two parts. The first part is actual revenue y; the second part is satisfaction revenue derived from resource utilization. High resource utilization indicates high user satisfaction with resources and a high degree to which the platform meets students' growth needs. Assuming the platform expects a resource utilization rate of $U_m(0 \le U_m \le 1)$, and the actual resource utilization rate is $U(0 \le U \le 1)$, if the platform perceives its revenue to be higher than the actual revenue when the rate is $U > U_m$, and lower than the actual revenue when the rate is $U < U_m$, this is reflected by the psychological incentive effect coefficient η_2. η_2 is related to the resource utilization coefficient μ_2 and the platform sensitivity coefficient $\mu_3(0 \le \mu_3 \le 1)$, set to $\eta_2 = \mu_2\mu_3$.

(5) Assuming that the platform's compensation to teachers is based on its psychological benefits, the platform's fine-tuning of actual benefits fully reflects its reward and punishment mechanism for teachers. When $U > U_m$, it indicates that the resources provided by teachers are sufficient, the platform's psychological benefits increase, and teachers receive higher compensation under the same β. When $U < U_m$, it indicates that the resources provided by teachers are slightly insufficient, the platform's psychological benefits decrease, and teachers receive lower compensation under the same β. Let the reward and punishment intensity coefficients be $\rho_2(0 \le \rho_2 < 1)$, $\lambda = \frac{U - U_m}{U_m}$, and $-1 \le \lambda \le 1$, and the resource utilization coefficients be $\mu_2 = \ln(1+\rho_2\lambda)$, $\frac{d\mu_2}{d\lambda} = \frac{\rho_2}{1+\rho_2\lambda} > 0$, and $\frac{d^2\mu_2}{d\lambda^2} = -\frac{\rho_2^2}{(1+\rho_2\lambda)^2} < 0$. That is, rewards increase as the gap between actual utilization rate and expected utilization rate widens, but the rate of increase slows down. When $\lambda \ge 0$, $0 \le \mu_2 < 1$, then $0 \le \eta_2 = \mu_2\mu_3 < 1$, indicating that the platform's psychological benefits increase. When $\lambda < 0$, $-1 < \eta_2 = \mu_2\mu_3 < 0$, indicating that the platform's psychological benefits decrease.

(6) The platform's final revenue is π, and the revenue function for teachers is $s(\pi) = \beta\pi$.

(7) Assume that the model satisfies the participation constraint, i.e., the utility ω that teachers obtain from participating in sharing is greater than their retention utility ϖ (the expected revenue of teachers). The model satisfies the incentive compatibility constraint.

(8) Assuming that the participation constraint and incentive compatibility constraint are satisfied, teachers are willing to share resources. The platform's problem is to select an incentive contract that satisfies the teachers' participation constraint and incentive compatibility constraint to maximize its expected utility function.

II. C. 2) Incentive model based on agency theory

The modeling steps based on the principal-agent model are as follows:

Step 1: Analyze and establish the functional relationship between the principal's revenue and the agent's effort.

According to the hypothesis, the platform's final revenue

$$\begin{aligned}\pi &= (1-\beta)(y(1+\eta_2)-S) \\ &= (1-\beta)((a_m^\alpha a_s^{1-\alpha}+\theta)(1+\eta_2)-S)\end{aligned} \tag{9}$$

Then the expected utility of the platform equals the expected return.

$$E_\pi = (1-\beta)\left(a_m^\alpha a_s^{1-\alpha}(1+\eta_2)-S\right) \tag{10}$$

Step 2: Analyze and construct agent participation constraint expressions.

Teacher's benefits

$$\begin{aligned}\omega &= s(\pi)(1+\eta_1)-C \\ &= \beta\left(\left(a_m^\alpha a_s^{1-\alpha}+\theta\right)(1+\eta_2)-S\right)(1+\eta_1)-\frac{1}{2}b\left(a_m^2+a_s^2\right)\end{aligned} \tag{11}$$

The expected utility of teachers equals the expected benefits of teachers.

$$E_w = \beta\left(a_m^\alpha a_s^{1-\alpha}(1+\eta_2)-S\right)(1+\eta_1)-\frac{1}{2}b\left(a_m^2+a_s^2\right) \tag{12}$$

The incentive-constraint expression for teacher participation is

$$\beta\left(a_m^{\alpha}a_s^{1-\alpha}\left(1+\eta_2\right)-S\right)\left(1+\eta_1\right)-\frac{1}{2}b\left(a_m^2+a_s^2\right)\geq\varpi \tag{13}$$

Step 3: Analyze and establish the agent incentive compatibility constraint expression.

The teacher incentive compatibility constraint expression is

$$\max\left(\beta\left(a_m^{\alpha}a_s^{1-\alpha}\left(1+\eta_2\right)-S\right)\left(1+\eta_1\right)-\frac{1}{2}b\left(a_m^2+a_s^2\right)\right) \tag{14}$$

Step 4: Based on the interests of the agent, the principal begins to consider the composition of their own pure interests and pursues their maximization. The platform's expected return $E_{\pi}=\left(1-\beta\right)\left(a_m^{\alpha}a_s^{1-\alpha}\left(1+\eta_2\right)-S\right)$ is to pursue the maximization of its interests, even if it tends toward the maximum, i.e.:

$$\max\left(\left(1-\beta\right)\left(a_m^{\alpha}a_s^{1-\alpha}\left(1+\eta_2\right)-S\right)\right) \tag{15}$$

Combining the platform revenue maximization function, participation constraints, and incentive constraints forms an incentive model:

$$\max\left(\left(1-\beta\right)\left(a_m^{\alpha}a_s^{1-\alpha}\left(1+\eta_2\right)-S\right)\right) \tag{16}$$

$$s.t.\begin{cases}(IR)\beta(a_m^{\alpha}a_s^{1-\alpha}(1+\eta_2)-S)(1+\eta_1)-\dfrac{1}{2}b(a_m^2+a_s^2)\geq\varpi\\(IC)\max(\beta(a_m^{\alpha}a_s^{1-\alpha}(1+\eta_2)-S)(1+\eta_1)-\dfrac{1}{2}b(a_m^2+a_s^2))\end{cases} \tag{17}$$

III. Simulation and performance analysis of sports resource information integration system

Based on the "neighborhood propagation clustering algorithm" and "agency incentive model" constructed in Chapter 2, this chapter verifies their practical effectiveness through simulation experiments. Using the ice and snow resources of universities in Heilongjiang Province as a sample, a resource integration system is designed and compared with multi-dimensional performance indicators to empirically test the feasibility of the theoretical model in improving resource sharing efficiency and reducing transmission losses.

III. A. Simulation experiment of sports resource information integration system

The core of this article's experiment lies in verifying the effectiveness and feasibility of the resource integration and sharing method proposed in this paper, which is based on a neighbor propagation clustering algorithm and a resource sharing incentive model. The experiment involves setting up a server cluster, configuring high-performance storage and computing resources, and ensuring the stability of network communication to simulate the process of uploading, storing, retrieving, and sharing teaching resources (such as courseware, videos, documents, etc.). A sports teaching resource integration scheme is constructed, with a reasonable resource classification system and retrieval mechanism designed to achieve unified management and efficient access to resources. Based on this, a resource sharing interface is developed to support concurrent access by multiple users, ensuring the smoothness and security of resource access. Additionally, strict access control policies were implemented to allocate resource access permissions based on user roles and privileges, ensuring the lawful use of resources. Through testing, the resource sharing efficiency of the sports teaching resource integration and sharing method was comprehensively evaluated, thereby verifying the method's effectiveness and reliability.

III. A. 1) Simulation Environment and Parameter Settings

To test the performance of the method described in this paper in the application of digital sports resources in clustering and information integration, a simulation experiment was conducted using the ice and snow resources of universities in Heilongjiang Province as the research object. The experiment was designed using MATLAB and combined with an embedded bus scheduling method for sports teaching resource bus transmission control. The global iteration count for resource integration was set to 100 times. The sampling amplitude for digital sports learning and teaching resources was set to A1 = A2 = A3 = 1, The sampling frequency of digital sports learning and teaching resource information was 1087 Hz, and the spatial sampling rate of sports resource information was 23 kHz.

The types and quantities of sports teaching resources used in the experiment are as follows: (1) Electronic textbooks: 100 volumes, averaging 50 MB per volume, totaling approximately 5 GB; (2) Video courseware: 5,000 pieces, averaging 500 MB each, totaling approximately 2.5 TB; (3) Case studies: 500 pieces, averaging 1 MB each, totaling approximately 0.5 GB; (4) Online test question bank: 5,000 questions, averaging 1 KB each, totaling approximately 5 MB; (5) Interactive teaching tools: totaling approximately 2 GB.

III. A. 2) Analysis of System Resource Integration Results

Based on the above simulation environment and parameter settings, digital integrated teaching resource information scheduling was conducted using ice and snow sports resources from a university in Heilongjiang Province as sample data. The distribution of the original resource information sample data is shown in Figure 1.

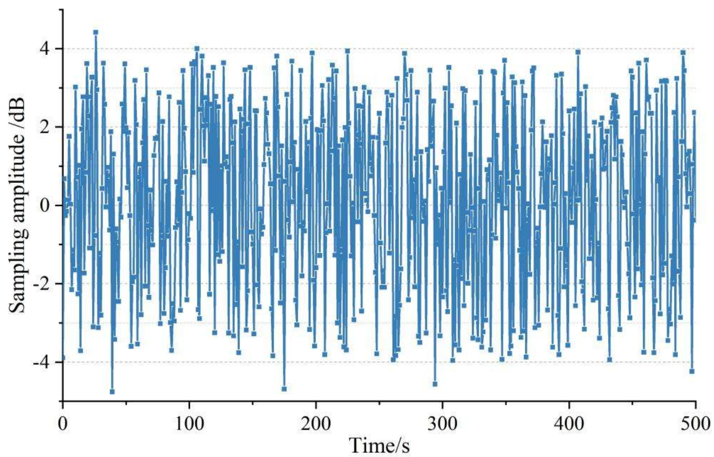

Figure 1: Original resource information sampling data distribution

Using the snow and ice sports resource information in Figure 1 as a test sample, resource integration processing was performed, and the integration results are shown in Figure 2.

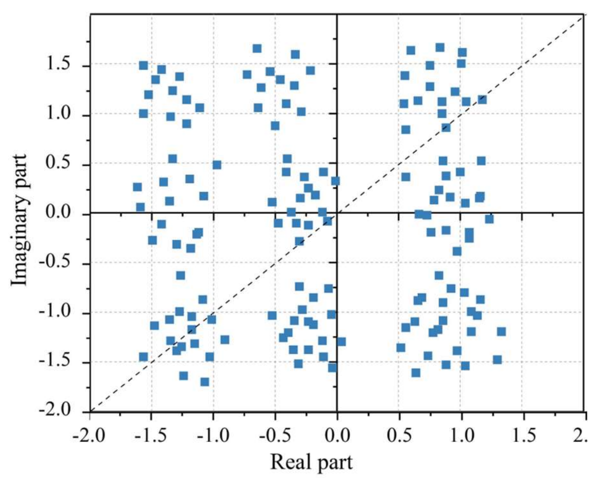

Figure 2: Resource integration and output

Analysis of Figure 2 shows that the method proposed in this paper achieves good balance in the integration of digital sports teaching resources under resource-driven conditions. Winter sports resources are effectively integrated and categorized, with no overlap between clusters, and the resource integration output is satisfactory.

III. B. Analysis of the effects of integration and sharing under different methods

After completing the system simulation environment setup and analysis of the results of basic resource integration, it is necessary to further quantitatively evaluate the comprehensive performance of the method proposed in this paper. Section 3.2 will conduct multi-dimensional verification through comparative experiments with mainstream methods, focusing on key indicators such as accuracy, sharing speed, and throughput.

To validate the superiority of the teaching resource integration and sharing method based on neighbor propagation clustering and resource sharing incentive models proposed in this paper, comparative experiments were conducted. Comparison method 1 is a cloud-based smart library literature resource integration and sharing method, and comparison method 2 is a cloud platform-based teaching resource integration and sharing method.

III. B. 1) Comparison of accuracy and recall in information integration management

The accuracy and recall of resource integration under different methods were tested, and the comparison results are shown in Figure 3.

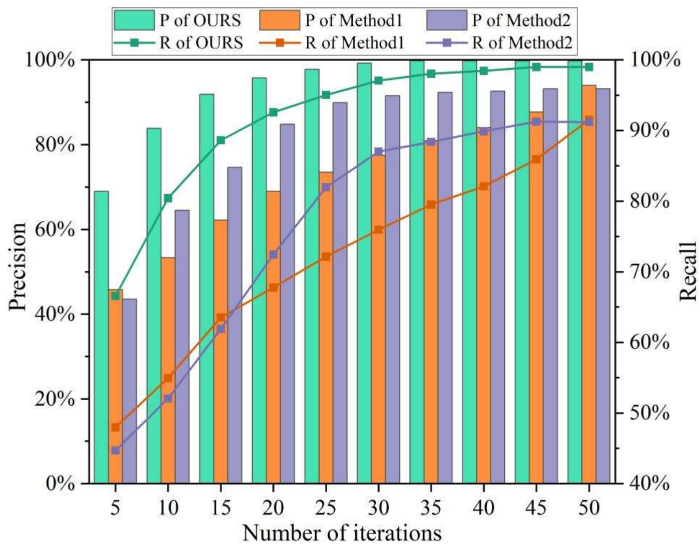

Figure 3: The precision and recall comparison of information integration management

As shown in Figure 3, the method proposed in this paper achieves stability by the 30th iteration, with precision and recall rates of 99.74% and 98.98%, respectively. In contrast, the cloud-based intelligent library literature resource integration and sharing method has not yet stabilized by the 50th iteration, with precision and recall rates of 93.95% and 91.52%, respectively; The precision and recall rates of the cloud-based teaching resource integration and sharing method 2 are 93.17% and 91.20%, respectively. After integrating digital sports teaching resource information using the method proposed in this paper, the precision and recall of information management are high, and the information integration performance is good.

III. B. 2) Comparison of resource sharing speeds

Information integration accuracy is only one dimension of performance evaluation; resource scheduling efficiency also affects user experience. The following section focuses on sharing speed in concurrent scenarios to reveal the responsiveness of the methods described in this paper under high load pressure.

The experiment simulated different numbers of user visits, conducted five experiments for each number of users, and recorded the average value. The resource sharing speeds of the three methods were recorded in detail and the results are summarized in Figure 4.

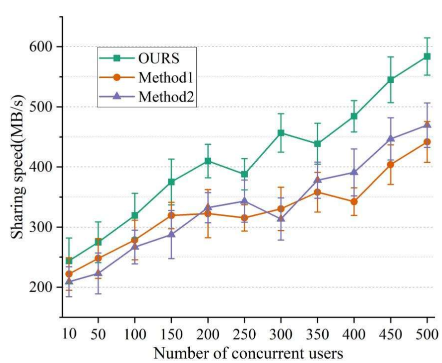

Figure 4: Comparison of resource sharing speeds under different numbers of users

As shown in Figure 4, the proposed method demonstrates excellent sharing efficiency under different numbers of concurrent users. When the number of concurrent users increases from 10 to 500, the sharing speed increases from 243.78 MB/s to 583.94 MB/s, showing an overall upward trend. Especially in high-concurrency scenarios with over 200 users, the proposed method consistently outperforms the comparison methods. For example, at 500 users, the proposed method achieves a resource sharing speed of 583.94 MB/s, while Method 1 only reaches 441.74 MB/s. As the number of concurrent users increases, the sharing speeds of all three methods fluctuate, but the advantage of the proposed method becomes increasingly evident.

III. B. 3) Throughput Comparison

To further validate the advantages of the method described in this paper, we compared the throughput of the three methods over different time periods. The system throughput was recorded every 5 seconds, and each method was tested five times to obtain an average value. The results are shown in Figure 5.

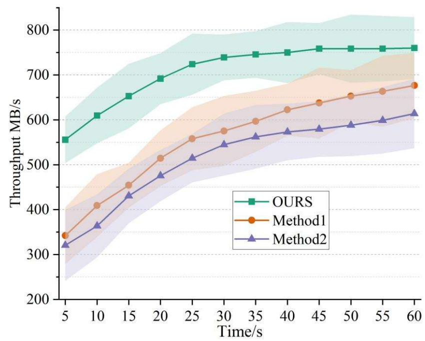

Figure 5: Comparison results of throughput for the three methods

As shown in Figure 5, under the same test conditions, the throughput performance of the proposed method consistently outperforms that of the comparison method. As the test duration increases, this advantage not only persists but also shows a trend of gradually strengthening. At 5 seconds, the throughput reaches 555.66 MB/s, and at 60 seconds, it reaches 760.05 MB/s, representing a growth rate of 36.8%. While the comparison method also improved (Method 1 increased from 342.02 MB/s to 676.47 MB/s), it remained consistently below the method proposed in this paper. For example, at the critical 30-second mark, the method proposed in this paper (739.08 MB/s) was 28.5% higher than Method 1's 575.17 MB/s. This result strongly demonstrates that the method proposed in this paper achieves extremely high sharing efficiency when handling complex scenarios such as high concurrency and large data volumes.

III. B. 4) Comparison of resource loss situations

Throughput metrics validate the system's processing capacity. This section conducts a loss rate analysis to examine the robustness of the proposed method in terms of data security transmission.

We tested the data loss rates of the three methods during resource transmission and sharing. A total of 500 pieces of data related to snow sports teaching were used to calculate the number of lost digital teaching resources under different numbers of concurrent users. The results are shown in Figure 6.

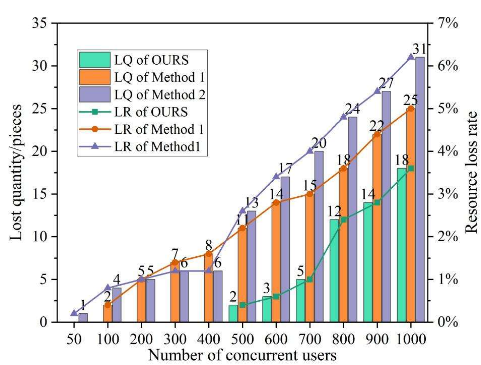

Figure 6: The amount of resources lost in integrated sharing under three methods

The method described in this paper demonstrates exceptional performance in resource loss control. It achieves zero loss under low concurrency (⩽300 users); even at high concurrency of 1,000 users, the loss rate is only 3.6% (18 entries), significantly lower than the 5.0% of Method 1 and the 6.2% of Method 2. In contrast, the comparison methods show a sharp increase in loss rates beyond 500 users. For example, Method 1 loses 25 packets at 1,000 users, while the proposed method maintains a loss rate below 12 packets until 800 users, highlighting its superior transmission stability.

III. B. 5) Comparison of teaching resource integration efficiency

The aforementioned experiments validated the overall performance, while the differentiated requirements of different types of resources are equally critical. Section 3.2.5 evaluates the integration efficiency by category, ultimately completing a comprehensive argument for the universality and specific advantages of the method.

A comparative analysis of the integration efficiency of different types of teaching resources was conducted, with the results shown in Figure 7.

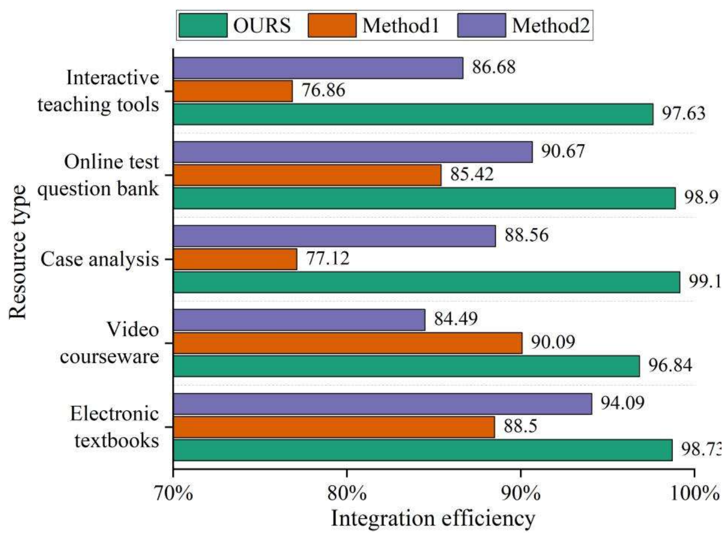

Figure 7: Comparison of integration efficiency of different types of teaching resources

The efficiency of the integration method used in this study exceeds 96% across all resource types. The integration efficiency of case studies reaches 99.17%, followed closely by electronic textbooks (98.73%) and question banks (98.91%). Comparative methods show varying performance. Method 1 achieves an integration efficiency of 90.09% for video lectures but only 77.12% for case analysis; Method 2 exhibits significant weaknesses in interactive tools (86.68%) and video lectures (84.49%), further validating the universal advantages of the method proposed in this paper.

IV. Conclusion

This study demonstrates an innovative path for the social development of winter sports in Heilongjiang Province by constructing a sports resource information integration system based on the neighbor propagation clustering algorithm and a shared incentive model.

The k-nearest neighbor clustering algorithm converges stably within 30 iterations, breaking through the limitation of traditional methods requiring over 50 iterations. Additionally, the error rate for clustering multi-dimensional heterogeneous resources (such as video lectures and interactive tools) is below 0.26%, significantly reducing the cost of manual intervention.

Under high concurrent pressure from 800 users, the resource loss rate of this method was only 12 entries, which is 50-67% of the comparison method, and the growth rate of the loss rate (at 1,000 users) was 28.9% lower than Method 1, validating the role of embedded bus scheduling in ensuring transmission integrity.

Structured resources (such as electronic textbooks and question banks) achieved efficiency rates exceeding 98.7%, while unstructured resources, particularly video lectures due to their large data size (average 500MB per file), saw efficiency drop to 96.84%. However, this still outperforms the comparison method by 12.35 percentage points, highlighting the algorithm's adaptability to heterogeneous data.

References

[1] Jing, Z. H. A. O., & Ziwei, L. I. (2024). Study on the Development of Ice and Snow Sports in China under the Background of Building a Leading Sports Nation. Journal of Chengdu Sport University, 50(4), 88-94.

[2] Jian-wei, D. E. N. G., Yu-fang, M. A., & Jia-lin, Y. I. (2022). The Strategy of Southward, Westward and Eastward Expansion of China's Ice and Snow Sports Development: Evolution Process and Connotative Value. China Sport Science, 42(7), 18-26.

[3] Chen, Z., Zuo, W., & Guan, H. (2023). Developing Sustainable Snow Sports Education Programs for Adolescent Participation. International Journal of Physical Activity and Health, 2(1), 27.

[4] Sun, Y. (2019). Research on the Promotion Approaches for Ice and Snow Sports on Campus. Frontiers in Sport Research, 1(2).

[5] Xu, L. (2022). Study on planning and design of ice and snow sports Tourism in Jilin Province under Changji-Tu Strategy. J. Educ. Hum. Soc. Sci, 5, 28-32.

[6] Jia, Q., & Fang, L. (2019). Research on the Problems and Countermeasures of Ice and Snow Sports Entering the Campus. Frontiers in Sport Research, 1(4).

[7] Sanzheng, C. H. E. N., Qing, Y. U. A. N., & Yonghong, H. U. (2022). From blank to reverse period: A cultural examination for the historical evolution of ice and snow sports in Guangdong. Journal of Physical Education/Tiyu Xuekan, 29(6).

[8] Qi, W. A. N. G., Ran, X. I. A., Jingzhan, L. I., Xin, X. I. A. N. G., Hongqin, C. H. A. I., & Hong, L. I. U. (2024). Research on Campus Ice and Snow Sports Policy in China from the Perspective of Policy Tools——An Analysis of 14 Campus Ice and Snow Sports Policy Texts since Winning the Right to Host the Winter Olympic Games. Journal of Chengdu Sport University, 50(4), 80-87.

[9] Li, X., Song, L., Wu, H., & Wang, Y. (2021). Optimization of ice and snow sports industry chain structure based on sensor network communication and artificial intelligence. Mobile Information Systems, 2021(1), 7267006.

[10] Li, C. (2018, November). Study on the Reference of Russian Ice-snow Sports Resources for the Cultivation of Ice-snow Sports Talents of Colleges and Universities. In International Conference on Contemporary Education, Social Sciences and Ecological Studies (CESSES 2018) (pp. 311-314). Atlantis Press.

[11] Bin, D. (2019). Research on the development of ice and snow tourism in Heilongjiang Province. International Core Journal of Engineering, 5(9), 180-183.

[12] Liu, C. (2024). Research and Application of Artificial Intelligence Technology in the Teaching of Ice and Snow Sports Mixed Courses in Universities. Journal of Social Science and Cultural Development, 1(1).

[13] Li, X. (2022, June). Research On Cultivation Mode Of" Ice And Snow" Applied Talents In Colleges And Universities. In Of Papers Presented at 2022 3rd Asia Sport Science Conference (ASSC).

[14] Zhang, L. (2011). Ski Industry Effects of Opening Skiing Lessons in Heilongjiang Province University and College. In Applied Economics, Business and Development: International Symposium, ISAEBD 2011, Dalian, China, August 6-7, 2011, Proceedings, Part I (pp. 475-479). Springer Berlin Heidelberg.

[15] Wu, X., & Liu, Z. (2020). Comparison on Curriculum Setting of Winter Sports in Universities in China, America and Europe. Open Journal of Social Sciences, 8(3), 529-539.

[16] Geng, L. (2020). Experimental Study on Common Skating Teaching Mode in Colleges and Universities. International Core Journal of Engineering, 6(7), 243-246.

[17] Hu, S. (2021). The Teaching Strategy of Ice and Snow Sports in Colleges and Universities from the Perspective of Sports Core Literacy. Frontiers in Sport Research, 3(1).

[18] Bozhkova, A., Ivanov, V., & Slavcheva-Hinkova, P. (2019). " Off campus training in Bulgarian language and sport" as a way for socialization and formation of community. Trakia Journal of Sciences, 17.

[19] Albayrak, A. Y., & Bayrakdaroğlu, Y. (2018). Assessment of socialization and sports-socialization processes of university students studying in different sports branches. International Journal of Educational Methodology, 4(2), 95-100.

[20] Chen, B., Han, S., Wang, H., Huang, X., & Wang, F. (2023). A study on the behavior intention of university students participating in winter sports. Heliyon, 9(7).

[21] Chengcai, T. A. N. G., Rui, Z. E. N. G., Yuanyuan, Y. A. N. G., Shiyi, X. U., & Xin, W. A. N. G. (2022). High-quality development paths of ice-snow tourism in China from the perspective of the Winter Olympics. Journal of Resources and Ecology, 13(4), 552-563.