Enhancing Informatization In Ice And Snow Sports Education Through Biological Principles And Hybrid Clustering Models

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The rapid expansion of ice and snow sports has highlighted critical challenges in the design and delivery of specialized curricula. Traditional teaching models often fall short due to fragmented structures, inconsistent resource allocation, and a lack of personalized, data-informed instructional strategies. This study proposes an intelligent, biologically-informed framework for optimizing ice and snow sports education by integrating innovation and entrepreneurship education, clustering algorithms, and big data analytics. We first explore the application of fuzzy c-means (FCM), optimized K-means, and hybrid metaheuristic algorithms in the evaluation and classification of informatization levels across specialized sports schools. Data were collected through nationwide surveys and processed using orthogonal matching pursuit and min-max normalization for standardization. Results from clustering and dimensionality reduction reveal three distinct levels of informatization application, supporting a more tailored educational model. Moreover, by embedding biological principles—such as individualized performance feedback and recovery analysis—into curriculum evaluation, the study enhances personalization and ecological adaptability in sports education.

Keywords: Intelligent Transformation; Ice and Snow Sports; Biomechanical Education; Innovation and Entrepreneurship; Curriculum Optimization

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1. Introduction

The rapid growth of ice and snow sports underscores the need to optimize educational curricula to meet the evolving demands of both competitive athletes and recreational participants [1, 2]. The development of winter sports in different countries requires the establishment of specialized training centers which provide dedicated programs for developing athletes. The educational programs face multiple challenges because they lack proper resources and their evaluation methods are ineffective while their technology systems and biological systems fall short of required standards [3, 4]. While many educational institutions recognize the importance of technology in sports training, few have effectively incorporated these tools into their curricula. The field of biology especially human physiology and performance enhancement techniques functions as a fundamental component of sports education. The understanding of training responses together with recovery processes enables the development of training programs which optimize nutrition and reduce injuries while enabling students to achieve their individual workout goals based on their specific needs and characteristics. Additionally, the concept of sustainable development in the context of biological systems highlights the importance of incorporating environmental, health, and technological considerations into educational models. This means that curricula should not only focus on physical training but also address the broader implications of sports on health and the environment. Such integration ensures the long-term viability of ice and snow sports [5–8].

The ice and snow sports programs develop new training methods which create sustainable events and performance technologies. The combination of clustering methods and fuzzy c-means system enables data-driven curriculum design which meets current industry requirements [9, 10]. The systems need to analyze athlete performance data together with educational data to discover trends while using biological principles and entrepreneurship education and FCM analytics to develop better curriculum and personalized training solutions [11, 12]. The application of intelligent, data-driven, and biologically informed approaches seeks to create a sustainable and innovative framework for ice and snow sports education. This model emphasizes continuous improvement, where feedback loops allow for real-time adjustments to training programs based on athlete performance and recovery data. This approach not only enhances the learning experience for students but also contributes to the overall development of ice and snow sports as a discipline. The system continuously gathers performance data from wearable sensors, training logs, and school platforms to enable real-time monitoring, adaptive instruction, and evidence-based curriculum improvement. Machine learning analytics combined with physiological monitoring support personalized training and intelligent management of ice and snow sports education [13]. Wearable technology facilitates continuous physiological tracking, real-time assessment, injury prevention, and biologically driven training optimization [14]. Artificial neural networks analyze IMU sensor data to accurately evaluate performance and identify movement patterns. Overall, the framework enables intelligent assessment, personalized training, and data-driven optimization in biologically informed and informatized sports education [15]. Grandhi et al. present a wearable monitoring system that tracks athletes' physiological signals to support real-time health assessment and risk detection. The proposed work develops an informatized sports education framework that combines biological indicators from athletes to achieve personalized training and safety improvements and sustainable athlete development [16].

The curriculum integrates physiological profiling and performance-based monitoring to design individualized training programs based on age, gender, adaptability, and recovery patterns. It evaluates endurance, neuromuscular coordination, fatigue response, and recovery indicators to optimize athlete development while preventing injury and overtraining. Environmental, health, and technological factors are combined to promote sustainable training systems, especially in ice and snow sports, emphasizing ecological adaptation and energy-efficient practices. The study applies clustering methods, including FCM, optimized K-means, and hybrid metaheuristics, to assess institutional readiness and informatization indicators. This data-driven framework supports personalized learning paths, effective resource allocation, and improved educational and athletic outcomes.

The study aims to evaluate the informatization level of ice and snow sports education institutions using clustering-based analytical methods. The research uses K-means and fuzzy clustering methods to classify schools according to their differences in three aspects which include infrastructure and teaching and management informatics systems. The study integrates biological system principles with ice and snow sports education to create performance-oriented adaptive sustainable curriculum development methods.

2. Materials and methods

2.1. Optimized clustering algorithm

When dealing with numerical data, the similarity measurement method presented in the following table prove to be quite useful. Among them, Minkowski distance is LP norm ($P \geq 1$), while Manhattan distance, Euclidean distance and Chebyshev distance correspond to the case when $p = 1$ or 2 respectively, as clearly shown in Table 1.

The integration of multiple algorithms in hybrid approaches inevitably increases algorithmic complexity. Thus, achieving a balance between algorithmic complexity and solution effectiveness remains a critical focus in the study of hybrid heuristic algorithms. To address this, a hybrid meta-heuristic algorithm, **m-ils-spp**, is proposed [17]. The algorithm employs multi-start and four neighborhood operators to enhance partition quality, integrating a Set Partition Problem model for global optimization, showing strong convergence [18, 19]. The system displays its structure through Fig. 1 which shows its initial highly computational needs and slow single-slice convergence, while the system uses refinements to achieve better operational performance with reduced system complexity.

The K-medoids algorithm uses "school grouping first, students assigning" to create school clusters which are then divided into multiple schools through hybrid heuristics to generate the best educational program, heuristic algorithms solve high-dimensional problems by using iterative rule applications to create approximate solutions which maintain computational efficiency and solve nonlinear constraints. The system needs initial values to operate but it faces two major problems because it attempts to find local solutions while processing complex datasets. This chapter proposes three hybrid heuristic algorithms to solve the

Table 1. Similarity measurement criteria function table.

Similarity measurement criteria	Similarity measure function
Euclidean distance	$d(x, y) = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2}$
Manhattan distance	$d(x, y) = \sum_{i=1}^{n} \|x_i - y_i\|$
Chebyshev distance	$d(x, y) = \max_{i=1,2,\ldots,n}^{n} \|x_i - y_i\|$
Minkowski distance	$d(x, y) = \left[\sum_{i=1}^{n}(x_i - y_i)^p\right]^{\frac{1}{p}}$

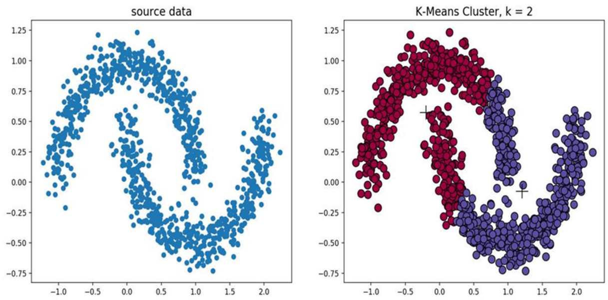

Fig. 1. Dimension code diagram.

school district division problem under the multi start and random mechanism [20].

The three hybrid heuristic algorithms employed in this study are described as follows:

- The multi-start K-medoids algorithm creates multiple distinct initial school groups which lead to decreased dependence on centroids and better capability to conduct global searches.
- The m-ils-spp solution uses iterative local search together with set partition modeling to improve optimization results while preventing premature algorithm termination.
- The hybrid neighborhood search method enhances both single school partitioning with multiple school partitioning processes by delivering stable as well accurate clustering results.

Three hybrid heuristics enhance clustering stability through their three methods which include K-medoids multi-start and (m-ils-spp) global optimization and hybrid neighborhood search that boosts both convergence rates and partitioning accuracy. The hybrid heuristic system unites separate algorithms to solve its three problems which include creating better search methods while preventing local search results and generating various solutions. All three follow identical structures: initial solution construction, hybrid optimization process, and final optimal solution generation.

2.2. Optimize clustering algorithm to build ice and snow characteristic teaching model

The effect of the original K-means source code test data is shown in Fig. 2 below.

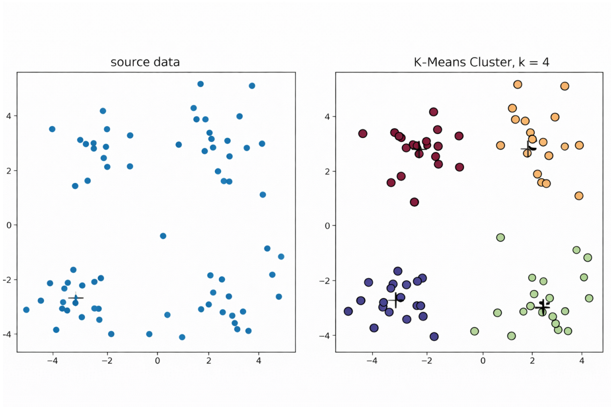

Fig. 2. K-means source code dataset.

Optimized fuzzy clustering guides ice-snow teaching; fuzzy set theory mathematically models ambiguous linguistic information and evolved through extensive research development [21]. On this basis, the objective function can be written as the following Eq. (1):

$$\min \sum_{i=1}^{n} \min_{j=1,2,\ldots,k} \left\| x_i - \mu_j \right\|^2 \tag{1}$$

This function is a non-convex optimization function and will converge to the local optimal solution, as shown in Eq. (2):

$$z = \min_{j=1,2} \left\| x_i - \mu_j \right\|^2 \quad (2)$$

The data of the optimized clustering algorithm should be classified into one category, while the data above should be classified into two categories, which is caused by the unreasonable selection of the initial centroid. Similarly, take the data set in the above figure, and take k = 2, 3, and 4 to get the following clustering results, as shown in Fig. 3.

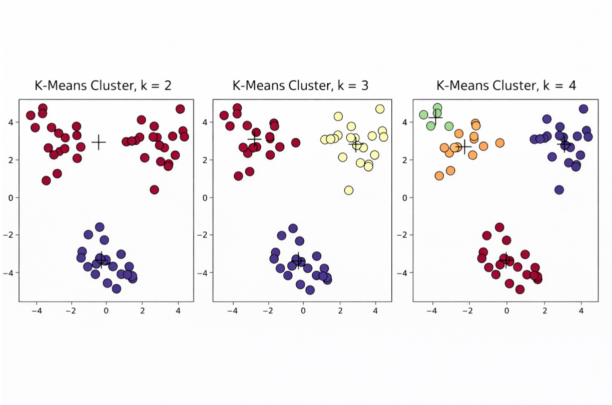

Fig. 3. Optimized source code data set 4 case study.

This chapter emphasizes data cleaning and standardization in constructing the ice and snow characteristic school model. The study exported questionnaire data on informatization levels and organized it but manual entry errors created inconsistencies and missing values and unreasonable inputs which required preprocessing to achieve accurate clustering and analysis results. The framework combines data from wearable sensors with academic records and behavioral logs. The datasets after cleaning and normalization process enable both clustering and assessment which allows for training intensity and teaching strategies and learning activities to be adjusted.

2.3. Sustainability- and Biology-Informed Curriculum Optimization Framework

Environmental sustainability improves educational programs through three waste management systems which include informatics-based resource control and facility scheduling and energy-consuming ice and snow equipment distribution. Clustering matches teaching requirements with available resources which leads to decreased resource wastage and reduced costs. Biologically informed training uses three methods which include physiological adaptation and recovery regulation and workload control. The system provides personalized feedback which helps users control their training intensity and rest periods while maintaining training limits and protecting against injuries and reducing reliance on energy-intensive training facilities for environmentally friendly sports education.

2.4. Operationalization of Biological Principles in the Clustering Framework

Biology provides measurement systems which research use to evaluate clustering methods. The training design process uses physiological adaptation principles together with recovery regulation methods and workload distribution methods to create input features used in performance analysis. The research uses optimized K-means and fuzzy c-means for clustering while biological principles guide the creation of indicators and the special educational assessment process. Biologically informed education integrates physiology, adaptation, recovery, and workload regulation into curriculum design. The system establishes training programs through biological constraints that determine both training intensity and rest periods and training sequences. The educational framework establishes operational boundaries based on physiological capabilities which help students avoid injuries while using traditional data analysis methods and sports education.

3. Results and discussion

The analysis begins after the questionnaire data has been exported and all invalid, missing, and duplicate entries have been eliminated. Based on informatization levels in ice and snow teaching schools [22, 23], each school serves as the survey unit, with the principal or information office director completing one questionnaire to report specific informatization application index data accurately and consistently [24].

As shown in Fig. 4, it is the data cleaning module of orthogonal matching pursuit.

3.1. Strengthen the application of data standardization

The study uses min-max normalization to achieve dimensionless scaling because multiple informatization indicators need standardization for proper clustering and analysis execution. The transformation formula is:

$$X_n = \frac{X - X_{\min}}{X \min_{\max}} \quad (3)$$

3.2. K-means clustering analysis to improve the informatization application

Enhancement of the K-Means method of multi-dimensional optimization under hard clustering in terms of distance appears in Fig. 5.

Data were collected through a questionnaire which evaluated 13 informatization indicators in ice-snow schools.

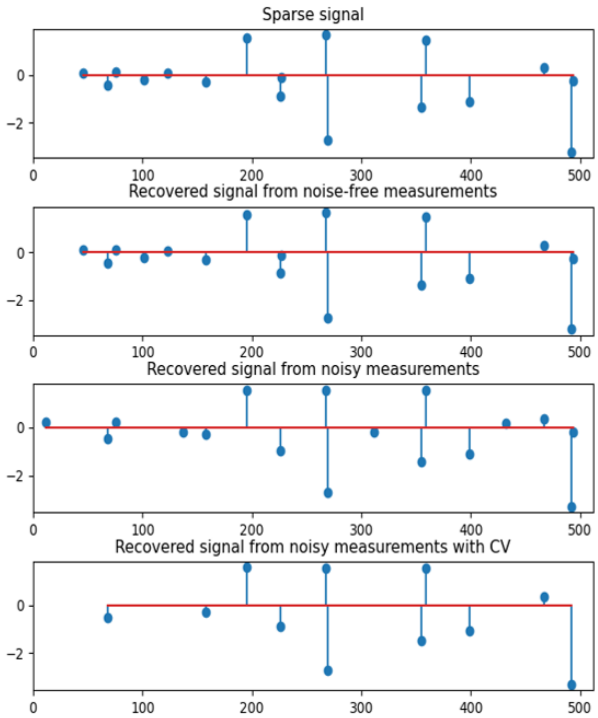

Fig. 4. Data cleaning module of orthogonal matching pursuit.

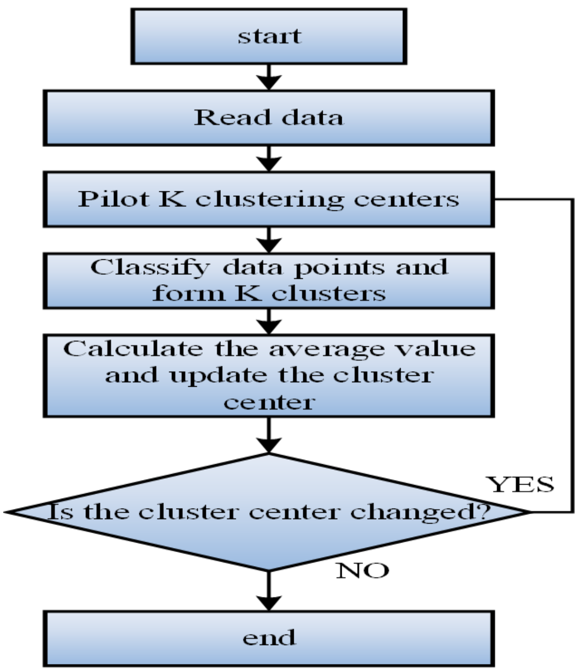

Fig. 5. Implementation flow chart of K-means clustering analysis algorithm.

The process of dimensionality reduction created a visual representation which showed different clusters [25]. Principal Component Analysis (PCA) reduces high-dimensional data by transforming NN dimensions into mm orthogonal principal components, preserving key features. For visualization purposes, the value of mm is normally set to 2 which allows complete two-dimensional display of the main data elements. The PCA method converts interconnected informatization indicators into distinct orthogonal components which maintain existing variance and create superior conditions for separating different groups in a school study. The Silhouette Coefficient measured between -1 and 1 found that clustering performed best at K=3 because SC value reached approximately 0.95. The value confirmed that schools organized into three separate informatization categories.

The clustering visualization results obtained using the K-means algorithm are presented in Fig. 6, highlighting the successful classification of informatization development levels within the dataset.

3.3. Optimized K-means

The highest number of schools exists in Category 2 which Fig. 7 uses to show development levels from three categories through 13 informatization application indicators that it presents for comparison.

As shown in Fig. 6, framework establishes three indicators which include A1 to A3 as infrastructure indicators and B1 to B7 as teaching informatization measures and C1 to C3 as management informatization evaluation criteria for schools that offer ice and snow sports programs. The study shows different educational institutions through its analysis of digital infrastructure and technology-based teaching methods and training programs which use biological knowledge. The three schools demonstrate identical infrastructure, but their multimedia resources reach 80% usage, while their computer labs and multifunctional classrooms require expansion to maintain educational standards. As shown in Table 2.

4. Conclusions

This study develops an integrated framework which combines biological systems with an algorithmic system to implement FCM and K-means and optimization methods together with survey indicators and performance metrics for categorizing three levels of informatization which support customized learning and continuous assessment and personalized evaluation and long-term technology-based educational development. The future work will develop adaptive learning systems which will incorporate wear-

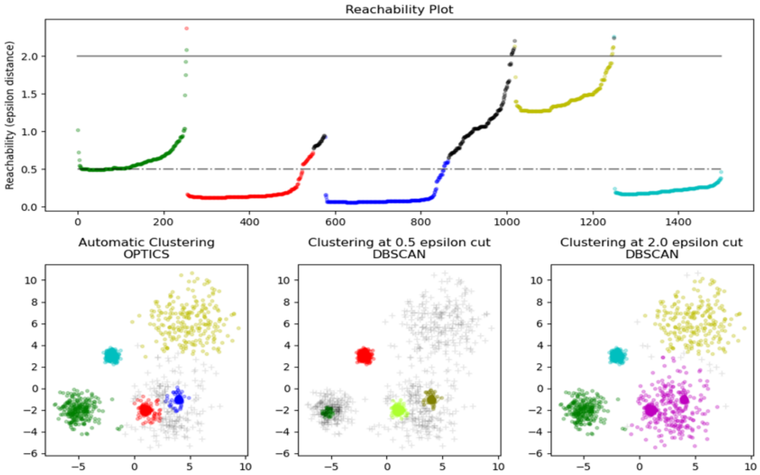

Fig. 6. K-clustering visualization effect of means clustering algorithm.

Table 2. Analysis results informatization application of different types of schools under K-means clustering.

		Sum of squares	df	mean square	F inspection	Scheffe (c)
Common functions of school online learning space	Intergroup	6.241	2	3.211	59.318	3 > 1
	In group	17.862	330	0.054		3 > 2
	total	24.284	332			1 > 2
Common functions of school teaching information system	Intergroup	7.934	2	3.967	71.182	1 > 2
	In group	18.391	330	0.056		1 > 3
	total	26.325	332			3 > 2
Proportion of teachers who open real name online learning space	Intergroup	56.887	2	28.444	808.012	1 > 2
	In group	11.617	330	0.035		1 > 3
	total	68.504	332			3 > 2
Proportion of subject teachers who can use information technology to teach	Intergroup	4.202	2	2.101	31.786	1 > 2
	In group	21.810	330	0.066		3 > 2
	total	26.011	332			
Functions of management information system commonly used in schools	Intergroup	16.876	2	8.438	25.200	3 > 1
	In group	24.471	330	0.074		3 > 2
	total	41.347	332			

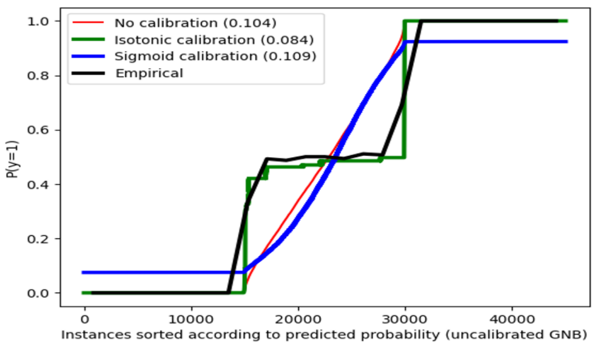

Fig. 7. K-development level under the informatization application index of means clustering.

able physiological monitoring systems and enhance cross-disciplinary collaboration.

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Declarations

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Data Availability

The data that support the findings of this study are not publicly available due to confidentiality agreements but are available from the corresponding author upon reasonable request.

Ethical approval

Not applicable.

Conflict of interest

The author declares no conflict of interest.

Author's Contributions

Chao Song is responsible for designing the framework, analyzing the performance, validating the results, writing the article, collecting the information required for the framework, provision of software, critical review, and administering the process.

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