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An Innovative Approach to Physical Education Management Based on the Maximum Information Entropy Model

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Abstract

Due to the rapid development of modern technology, nowadays there is a need to process and analyze all types of student data and thus optimize physical education management methods. In this paper, the maximum information entropy model is proposed based on the information entropy model of fuzzy rough sets, and a new algorithm FS-mMc is designed based on this model. this algorithm is capable of processing mixed information such as discrete, continuous and fuzzy data simultaneously in order to calculate the entropy weight of each indicator and thus obtain the important factors that make students burnout. A comparison of the classification accuracy of this algorithm with CFS, Relief, and InfoGain algorithms under different conditions yielded that the accuracy of this algorithm improved by at least 16.42% over the other algorithms with at least half the number of features selected. In the analysis of the factors influencing students' burnout in physical education, the mean difference between male and female students in terms of gender was found to be 0.25, between freshmen and juniors in terms of grade was 0.36, between sophomores and seniors in terms of grade was 0.47, and between urban and rural areas in terms of difference was 0.26. Therefore, the algorithm proposed in this paper has a higher accuracy in data processing and analyzes the main factors influencing students' burnout in terms of factors, thus improving the physical education management ability.

Keywords: *physical education, influencing factors, maximum information entropy, fuzzy rough set*

Introduction

The era of knowledge economy makes the focus of international competition become the competition of economy and science and technology, and the key is the competition of talents, especially the competition of high quality talents (Dong Z, 2016; Kubai, Mwangi, & Owiti, 2021). Higher education, including sports, is responsible for cultivating innovative and complex talents, and the educational reform of colleges and universities determines the quality of talent cultivation (Druz, Iermakov, Artemyeva, Puhach, & Muszkieta, 2017; Lin, 2021). However, the status quo of physical education reform in colleges and universities is not optimistic and must be deepened (Richards, 2015). Modern education technology is accompanied by the development of information science and technology and soft science and technology, which is a product of the high development of recent science and technology, and it has changed the operation and development mode of various fields of society, changed the way of life and learning of the members of society, and brought a great impact to higher education including sports (Erfle & Gamble, 2015;

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Gao J, 2019). Full application of modern education technology is inevitable to deepen the reform of physical education in colleges and universities (Minin M. G, 2020; Мосійчук, 2020).

In terms of the physical education curriculum, the study of the British Educational Standards Agency in the literature (Beale et al., 2021) was directed to the aspect of the survey report in the curriculum supervision of school physical education, and the results of the study showed that the supervision of the implementation of the content of the supervision of the school physical education curriculum should include six main areas: achievement and standards, quality of teaching and learning subjects, quality of the curriculum, management of the subject, continuity of the various stages of school physical education and suggestions for improvement. The literature (Wang J Y, 2010) in the United States, in a study on the supervision of the school physical education curriculum, argues that credit should be earned by selecting physical education courses with supervision and suggests that the supervision of the physical education curriculum should be accomplished through the joint efforts of four parties: students, schools, supervisors, and society.

In terms of physical education safety, the literature (Yang & Li, 2018) school physical education safety supervision refers to the supervisory activities carried out in the school physical education business and the safety considerations in various activities, the educational injuries of students in school physical education, and the supervision of physical education teachers' demonstration in physical education teaching activities. In the literature (Oliiar, Havryliuk, Antonenko, Lopatenko, & Tymofieieva, 2020), the School Physical Education Safety Education Training Centre in the UK, through a study of safety supervision in school physical education supervision, concluded that the implementation of safety supervision should include the following main elements: "First, the desired purpose of the implementation of safety teaching supervision. Second, the way and method of implementing safety supervision. Third, the implementation of safety supervision to achieve a comprehensive effect. Fourth, the standards to be achieved by the implementation of safety supervision. Fifth, the quality of safety supervision on the effectiveness of physical education and training activities. Sixth, the leadership and management of school sports safety supervision. And gives the specific matters detailed in each part of supervision, and provides the evaluation criteria of supervision."

In terms of the objectives of physical education training students, the literature (E., 2016) found that the physical education profession in the United States is well developed, with clear objectives of talent training, professionalism and relevance. In terms of curriculum, the subjects are clearly classified and most of them focus on general studies, combining theory and practice, and focusing on students' internship ability. In the literature (Akiyama, 2020) Japan, in terms of training objectives, physical education teachers are trained to adapt to the needs of society, and the training objectives are constantly adjusted according to the needs of society. In terms of curriculum, the hierarchy is clear, the classification is concise, the emphasis is on practical technical classes that benefit students in the process of practice, and the emphasis is on the development of courses with the characteristics of the nation. In the literature (Martínez-Santos, Founaud, Aracama, & Oiarbide, 2020), the training objectives in the UK are broad, focusing on the cultivation of students' comprehensive quality of "multi-discipline" and striving to achieve the training goal of "thick foundation and wide caliber". In terms of curriculum, the basic courses and the study of students' research ability are emphasized to lay a solid foundation for students to learn professional skills, and corresponding courses are offered for students of different ages and special students.

In this paper, the maximum information entropy model is proposed based on the new fuzzy rough set information entropy model. According to its feature relevance definition retain its strong correlation characteristics, remove irrelevant features, and then propose a new feature selection algorithm FS-mMc. The algorithm uses heuristic forward search, initially for the empty set, and each time selects the attribute with the maximum mutual information to add to the feature subset. If the attribute increases the correlation entropy of the subset, i.e., the redundancy decreases, the attribute is retained, otherwise the attribute is removed, and so on repeatedly until the correlation entropy no longer increases and the algorithm stops. To verify the feasibility and selection effect of the algorithm, 12 datasets from the UCI database were used to test the algorithm. The selection results are compared with CFS, Relief and InfoGain algorithms to verify the accuracy of this paper's algorithm. Finally, burnout in student learning is analyzed to test its specific functions and key influencing factors are obtained by excluding useless data.

Maximum Information Entropy Model

Information entropy model of fuzzy rough set

Often rough data contains fuzzy information, and there is also rough classification in fuzzy data, about how to measure the uncertainty of the data, in 1999 Wierman proposed a definition of information entropy for measuring uncertainty of rough sets: Definition 1 Let U be a finite theoretical domain, R is an equivalence relation on U, and the equivalence division about R is $\{X_1, X_2, \cdots, X_k\}$, then the information entropy of the approximation space (U,R) is defined as:

$$E(R) = -\sum_{i=1}^{k} |X_i|/|U| \log_2 |X_i|/|U| \tag{1}$$

The definition reflects the amount of information in the coarse categories, but focuses only on the information within the categories, without considering how the information outside the categories is measured, so the definition is incomplete. In 2002, Jiye Liang defined a new information entropy model that considers the complementary set of category classification, see equation (2).

Definition 2 Let U be a finite theoretical domain, R be an equivalence relation on U, and the equivalence division on R be $\{X_1, X_2, \cdots, X_k\}$, then the information entropy of the approximation space (U,R) is defined as:

$$E(R)=\sum_{i=1}^{k}|X_i|/|U|(1-|X_i|/|U|) \tag{2}$$

The above definition is strict for relation R, and in many cases it is not guaranteed that R satisfies the equivalence relation, which cannot be adapted to the uncertainty measurement under fuzzy rough set conditions.

Definition 3 Let $U=\{X_1,X_2,\cdots,X_n\}$ be a finite theoretical domain and R be an arbitrary fuzzy relation on U, then the information entropy of the approximation space (U,R) is defined as:

$$H(R)=\sum_{i=1}^{n}1/|U|(1-|[x_i]R|/|U|) \tag{3}$$

Where: $|[x_i]R|=\sum_{j=1}^{n}r_{ij}$ denotes the potential of object x_i under the fuzzy relation R and r_{ij} denotes the similarity of the two objects.

Theorem 1 Let R be a self-adverse fuzzy relation on U, then:

The maximum value of $H(R)$ is $1-1/U|$, and:

$$H(R)=1-1/U|\Leftrightarrow[x_i]R=\{x_i\},\forall i\in n \tag{4}$$

The maximum value of $H(R)$ is 0, and

$$H(R)=0\Leftrightarrow[x_i]R=U,\forall i\in n \tag{5}$$

Theorem 2 Let R be an equivalence relation on U, then $H(R)=E(R)$.

Definition 4 Let U be a finite theoretical domain, P and Q be arbitrary fuzzy relations on U, $[x_i]P$ and $[x_i]Q$ are fuzzy equivalence classes generated by P and Q containing x_i, then the conditional entropy of P and Q is defined as:

$$H(Q|R)=\sum_{i=1}^{n}(1/|U|)(|[x_i]P-[x_i]Q|/|U|) \tag{6}$$

Definition 5 Let U be a finite theoretical domain, P and Q be arbitrary fuzzy relations on U, and $[x_i]P$ and $[x_i]Q$ be fuzzy equivalence classes generated by P and Q containing x_i, then the mutual information of P and Q is defined as:

$$I(Q;P)=\sum_{i=1}^{n}1/|U|(1-|[x_i]PU[x_i]Q|/|U|) \tag{7}$$

Feature Selection Algorithm Based on Maximum Information Entropy

Feature Correlation Definition

According to the feature relevance, the features can be classified into three categories, i.e., strongly correlated features, weakly correlated features and irrelevant features. Let the original feature set be $A=C\cup d$ and feature $a_i \in C, S$ be the selected feature subset, the relevance of the features is defined as follows:

Definition 6 If $I(d/S\cup a_i)\neq I(d/S)$, the feature a, is said to be strongly correlated.

Definition 7 A feature a is said to be weakly correlated if $I(d/S\cup a_i)\neq I(d/S)$, and $\exists S_i \subseteq S, I(d/S_i\cup a_i)\neq I(d/S_i)$.

Definition 8 If $\forall S_i \subseteq S, I(d/S_i\cup a_i)\neq I(d/S_i)$, then feature a_i is said to be irrelevant.

Strongly correlated features must be retained, otherwise they can seriously affect the classification performance. Weakly correlated features are not always required, but sometimes they are necessary, so they need to be traded off depending on the situation. Irrelevant features are not necessary to be retained at all and need to be removed.

Maximum mutual information and maximum correlation entropy criterion

The correlation definition can not only reflect the relationship between attributes, but also express the relationship between attributes and classes. The maximum correlation criterion in this paper is defined by the maximum mutual information between the conditional attributes and the decision attributes calculated according to equation (6), i.e., the maximum value of the mean value of the mutual information between a single attribute and a decision class in the genus subset as shown in equation (7):

$$\max M(S\cup a_i, d), M = 1/|S|\sum_{a_i\in S} I(a_i;d) \tag{8}$$

Although the more relevant attributes to the decision class are more discriminative, due to the mutual cross-redundancy among the selected attributes, often the most relevant subset selected is a suboptimal solution in constructing the classifier, and its classification accuracy may not be higher than that of the relatively less relevant subset of attributes. Therefore, the redundancy or independence between attributes must be considered so that the selected subset of attributes not only has strong relevance, but also the inter-attribute redundancy between attributes is minimized. For this purpose, the correlation entropy is used to measure the independence of the conditional attribute set, which is defined as follows:

$$H_{CE}(S) = -\sum_{i=1}^{N} \lambda_i/N \log\ N\lambda_i/N \tag{9}$$

where λ_i represents the i nd eigenvalue of the correlation coefficient matrix of the attribute set.

The higher the correlation entropy, the lower the correlation of the attribute set, i.e., the greater the independence. Conversely, the opposite is true. If all attributes are linearly correlated, then the correlation entropy is 0. If all attributes are independent, then the correlation entropy is l. For the selected set of attributes to have minimum redundancy, the following criterion of maximum correlation entropy must be satisfied:

$$\max H_{CE}\left(S \cup a_i\right) \forall a_i \in C - S \tag{10}$$

Feature selection algorithm model

A new feature selection algorithm, FS-mMC, is proposed based on the maximum information entropy feature selection algorithm standard MmiMce. The algorithm uses a heuristic forward search with an initial empty set, and each time the attribute with the maximum mutual information is selected and added to the feature subset. The algorithm stops when the correlation entropy no longer increases. The algorithm is described as follows:

$$\begin{aligned}
&\text{Algorithms : FS} - \text{mMC} \\
&\text{Input : Decision-making information systems DIS}\langle U, A, V, f \rangle, A = C \cup d \\
&\text{Output : Optimal subset of properties of the system} \\
&a) S = \varnothing, H_{CE}\left(S\right) = 0; \\
&b) \forall a_1 \in C - S, calculate\ M\left(S \cup a_i, d\right), \\
&Choose\ M\left(a\right) = \max M\left(S \cup a_i, d\right); \\
&c) Compute\ H_{CE}\left(S \cup a\right), \\
&\text{if } H_{CE}\left(S \cup a\right) - H_{CE}\left(S\right) > 0, \\
&\text{then } S = S \cup a, \\
&\text{else end;} \\
&d) \text{ return } S
\end{aligned}$$

To analyze the complexity of the algorithm, assume that there is a total of N conditional attribute and the time complexity of calculating the fuzzy relationship for each attribute is $O(N)$. The average time complexity is $O(N \log N)$, so the total time complexity of the algorithm is $O(N \log N)$.

Results and Analysis of Physical Education Based on the Maximum Information Entropy Model

Analysis based on the maximum information entropy model

To verify the feasibility and selection effect of the algorithm, 12 datasets from the UCI database

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are used to test the algorithm, as shown in Table 1, except for Bc and Lc which are purely symbolic data, all the datasets contain continuous data or mixed data.

Table 1: Information on the experimental UCI dataset

Dataset		Number of objects	Number of attributes				Category Number
Abbreviations	**Full Name**		Conditional Properties	Decision Properties	Numerical	Symbolic	
Bc	Breast cancer data	280	10	1	1	10	2
Wbe	Wisconsin breast cancer	700	10	1	10	1	2
Cre	German Credit	1000	20	1	8	15	2
Cle	Cleveland Clinic	300	15	1	6	8	2
Lc	Lung Cancer	35	55	1	1	55	5
Gla	Glass Identification	215	10	1	10	1	8
Iris	Iris Plants	150	5	1	5	1	3
Veh	Vehicle Silhouettes	950	20	1	20	1	5
Wat	Water Treatment 2	525	40	1	40	1	15
Win	Wine Recognition	180	15	1	15	1	5
Ion	Ionosphere	350	35	1	35	1	2
Wdbc	Wisconsin diagnostic breast cancer	570	30	1	30	1	2

The selection results were compared with CFS, Re-lief and InfoGain algorithms in conjunction with WEKA software developed by Waikato University, New Zealand, and the classification accuracy was evaluated for each feature subset of the dataset selected by each algorithm under C4.5, Bagging and Naive Bayes conditions, respectively, and the comparison results are shown in Table 2, Table 3 and Table 4. From the analysis in the table, we can see that each algorithm performs differently for different datasets. The InfoGain algorithm has the highest classification accuracy on some datasets but does not perform well on all datasets. InfoGain has the highest classification accuracy on the Bc dataset but performs average on other datasets, which is in line with the No Free Lunch theory that different algorithms usually have their own advantages and disadvantages, and no algorithm is absolutely better than another. The subset of features selected by each algorithm performs differently under different classifiers, e.g., the subset selected by the CFS algorithm performs average under the C4.5 condition, but performs relatively well under the

Bagging and Naive Bayes classifiers. However, it lags slightly under the Naive Bayes condition.

Table 2: Accuracy of the feature selection algorithm under C4.5 conditions

Data	Origin		CFS		Relief		InfoGain		FS-mMCF	
	Fn	Accu.	Fn	Accu.	Fn	Accu.	Fn	Accu.	Fn	Accu.
Bc	10	74.69	5	73.32	6	70.44	6	74.72	10	74.82
Wbe	10	94.65	10	94.75	9	94.47	8	94.54	8	95.23
Cre	20	71.04	5	73.66	8	71.69	10	72.6	5	72.86
Cle	15	52.23	10	54.14	5	53.52	10	54.25	5	57.02
Lc	55	50.04	10	65.72	12	65.81	15	62.42	10	68.73
Gla	10	65.92	8	69.71	5	71.92	8	69.58	5	69.75
Iris	5	96.15	2	95.96	2	96	2	95.96	3	96.16
Veh	20	72.4	10	68.25	10	70.21	10	66.55	8	69.45
Wat	40	81.12	10	82.99	10	83.3	10	83.28	10	83.86
Win	15	93.83	10	93.92	8	94.49	5	94.31	5	94.9
Ion	35	91.43	15	90.62	10	93.18	15	91.47	10	89.31
Wdbc	30	93.04	10	94.05	8	94.68	5	93.01	5	92.46
Ave.	22.08	78.05	8.75	79.76	7.75	79.98	8.67	79.39	7	80.38

Table 3 Accuracy of the feature selection algorithm under Bagging conditions

Data	Origin		CFS		Relief		InfoGain		FS-mMCF	
	Fn	Accu.	Fn	Accu.	Fn	Accu.	Fn	Accu.	Fn	Accu.
Bc	10	68.11	5	70.3	6	67.5	6	69.33	10	68.78
Wbe	10	95.42	10	95.65	9	95.44	8	95.41	8	95.45
Cre	20	74.24	5	74.83	8	74.47	10	74.34	5	74.76
Cle	15	43.89	10	46.74	5	46.24	10	43.92	5	59.53
Lc	55	46.81	10	53.3	12	53.07	15	56.32	10	62.59
Gla	10	71.51	8	71.33	5	73.27	8	71.6	5	72.3
Iris	5	94.16	2	94.77	2	94.67	2	94.56	3	94.09
Veh	20	73.3	10	69.45	10	72.19	10	68.56	8	72.61
Wat	40	72.33	10	85.49	10	84.49	10	72.4	10	85.81
Win	15	94.9	10	94.96	8	95.45	5	95.56	5	95
Ion	35	90.89	15	90.88	10	92.17	15	92.64	10	91.27
Wdbc	30	94.87	10	94.86	8	94.85	5	93.98	5	94.23
Ave.	22.08	76.70	8.75	78.55	7.75	78.65	8.67	77.39	7	80.54

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Table 4: Accuracy of the feature selection algorithm under Naive Bayes conditions

Data	Origin		CFS		Relief		InfoGain		FS-mMCF	
	Fn	Accu.	Fn	Accu.	Fn	Accu.	Fn	Accu.	Fn	Accu.
Bc	10	72.05	5	72.8	6	69.77	6	73.27	10	73.19
Wbe	10	96.17	10	96.06	9	96.26	8	96.13	8	96.35
Cre	20	75.14	5	73.19	8	75.76	10	74.6	5	75
Cle	15	55.85	10	57.45	5	57.41	10	57.07	5	61.05
Lc	55	59.42	10	71.93	12	75.13	15	74.86	10	81.38
Gla	10	49.48	8	47.95	5	44.94	8	48.23	5	48.27
Iris	5	95.84	2	96	2	95.86	2	95.97	3	95.33
Veh	20	44.92	10	48.41	10	40.98	10	42.68	8	45.6
Wat	40	83.71	10	86.64	10	85.9	10	84.68	10	85.88
Win	15	96.73	10	97.21	8	96.11	5	97.54	5	96.17
Ion	35	82.48	15	91.98	10	89.88	15	86.27	10	89.07
Wdbc	30	92.96	10	94.43	8	94.64	5	93.24	5	93.16
Ave.	22.08	75.40	8.75	77.84	7.75	76.89	8.67	77.05	7	78.37

Although the algorithm in this paper may not perform as well as the other three algorithms on some datasets, such as lon and Wdbc, in general, FS-mMC performs more consistently and has the highest classification accuracy on nearly half of the datasets, and obtains the highest average classification accuracy under C4.5, Bagging and NaiveBayes conditions, as shown in Figure 1. In particular, the performance improvement is more obvious on data sets such as Cle, Lc. As shown in Table 3 for Cle, FS-mMC improves the accuracy by 16.42% over other algorithms with at least half the number of selected features. In Table 4, for Lc, the algorithm improves the accuracy by 8.97% while reducing the number of features in the subset by almost half.

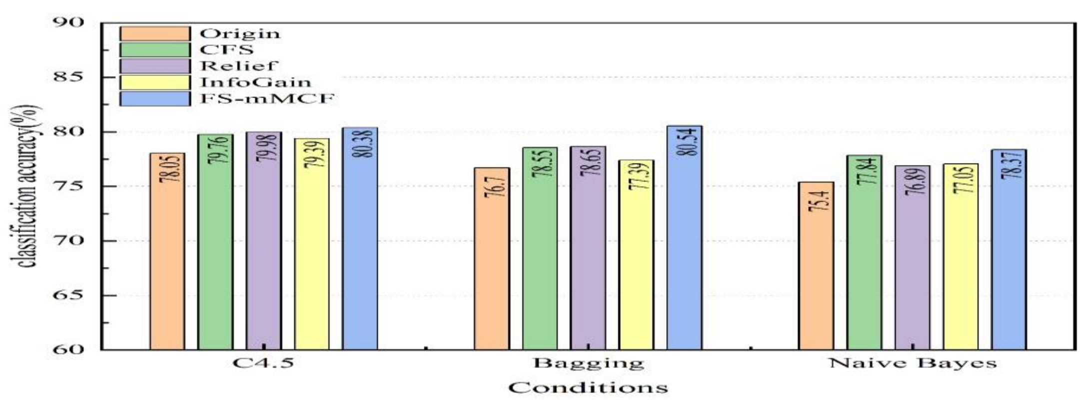

Figure 1: Comparison of average accuracy of algorithms

The classification accuracy of the selected subset is an important aspect of feature selection, and also the number of features contained in the selected subset should be considered, i.e., whether the algorithm can select as few features as possible while maintaining a high classification accuracy. The comparison of the number of features in the subset selected by the algorithms is shown in Figure 2. The subset selected by the algorithm in this paper contains the least average number of features, which is 7 on average, and it is 63% simpler compared to the original features, and at least 15.1% simpler compared to other algorithms, and the accuracy is also improved.

From the above analysis, it is known that the FS-mMC algorithm is stable and effective compared to the other three algorithms because the selected subsets have a higher average classification accuracy while maintaining the selection of a smaller number of features.

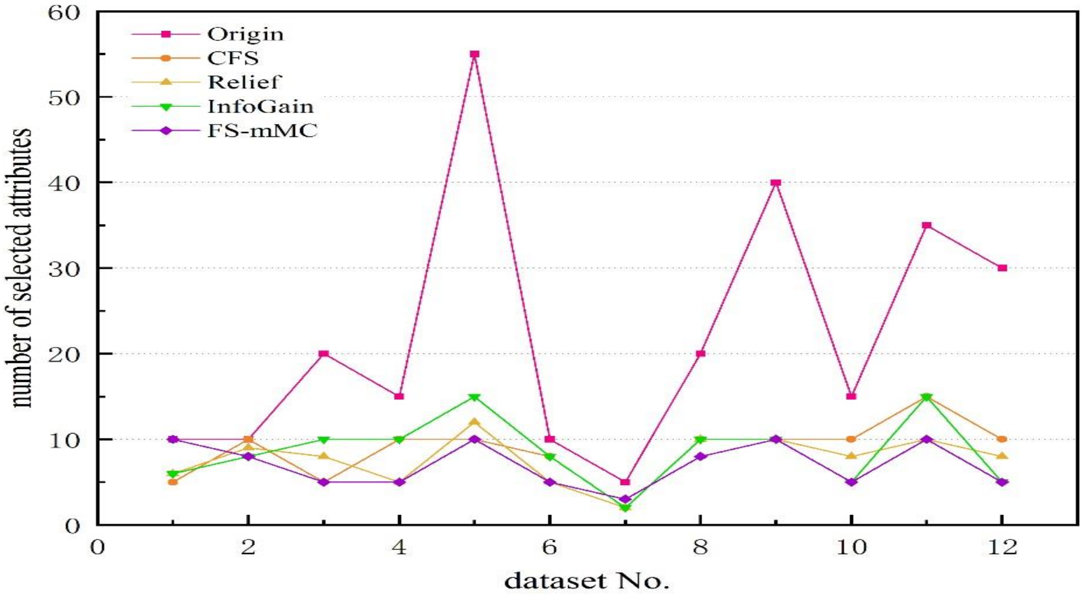

Figure 2: Comparison of the number of subset features selected by the algorithm

Study burnout among physical education college students

The FS-mMc approach based on the maximum information entropy model was used to organize and summarize the obtained student data, and as seen in Table 5, the mean score of the level of learning burnout of physical education college students is lower than 3, which shows that the level of learning burnout of physical education college students is at a moderate to low level.

From the three dimensions of learning burnout, it seems that low emotion (M=2.81) > low achievement (M=2.68) > inappropriate behavior (M=2.65) with standard deviation less than 1, indicating that the overall variability of the subjects' responses related to each dimension of learning burnout is not significant.

By logically sorting out the inverse relationship between each dimension and the good level, it is clear that the appearance of inappropriate behaviors such as skipping class, leaving late and early, playing with cell phones or sleeping in class under the misbehavior dimension is the main factor in the formation of students' learning burnout situation.

Table 5: Descriptive analysis table for each dimension of learning slackness

Dimensionality	M±SD
Learning Burnout	2.67±0.7
Depressed mood	2.81±0.63
Misbehavior	2.65±0.64
Low sense of accomplishment	2.68±0.53

Gender differences in learning burnout among physical education college students

In order to make a better study and judgment on students' learning burnout, the influence of gender on the learning burnout of physical education college students was studied. The FS-mMc method based on the maximum information entropy model was used to compare and analyze the influence of gender differences on the learning burnout of physical education college students, and the results are shown in Table 6.

Physical education college students' learning burnout was associated with gender differences. Analysis of the data in the table shows that there is no significant difference in the dimension of low mood ($P>0.05$) as well as the dimension of inappropriate behavior ($P>0.05$) of learning burnout among physical education majors with different genders.

Whereas, there was a significant difference in the effect of gender difference on learning burnout on the low achievement dimension ($p<0.05$).

With regard to the data obtained, the effect of gender differences on burnout was not significant in the low mood dimension (male: 2.7, female:2.63, mean difference:0.12, $p>0.05$) and in the inappropriate behavior dimension (male:2.96, female:2.87, mean difference:0.17, $p>0.05$), thus indicating that the gender differences in the formation of The main cause of the burnout problem is not in the emotional depression dimension and the inappropriate behavior dimension of burnout.

However, in the low achievement dimension of learning burnout, there is a significant difference between male and female students in terms of gender difference on learning burnout (male: 2.67, female: 2.45, mean difference: 0.20, $p<0.05$), so it can be inferred that the main reason for the generation of learning burnout among physical education college students in Liaoning Province is the low achievement dimension of learning burnout, which is affected by gender difference.

The main reason for the formation of this phenomenon may be due to the fact that the students of physical education in Liaoning Province have a low level of achievement.

The reason for the formation of this phenomenon may be due to the fact that female students

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among college students have better learning attitudes and learning behaviors than male students, which leads to better performance than male students, and therefore the score of low sense of achievement is lower than that of male students, thus promoting their learning to be more active and positive.

Table 6 Comparison of gender differences on the dimensions of learning burnout

Dimensionality	**Male(n=3655) M±SD**	**Female(n=3655) M±SD**	**Mean Difference**	**T**	**P**
Study Burnout	2.71±0.47	2.66±0.54	0.13	1.638	P>0.05
Depressed mood	2.7±0.73	2.63±0.68	0.12	0.674	P>0.05
Inappropriate behavior	2.96±0.62	2.87±0.67	0.17	0.894	P>0.05
Low sense of accomplishment	2.67±0.68	2.45±0.57	0.20	2.214	P<0.05

Grade differences in learning burnout among physical education college students

In order to make a better study and judgment of students' burnout, the effect of grade level on the burnout of physical education college students was studied. The results of the F-test on the influence of grade differences on the learning burnout of physical education college students are shown in Tables 7 and 8.

It can be seen that the burnout status of college students in different grades of physical education majors on the low mood dimension of learning burnout was: junior (M=2.94) > sophomore (M=2.71) > freshman (M=2.63) > senior (M=2.58).

In addition, the LSD multiple comparisons of physical education college students in different grades on the low mood dimension in Table 8 show that there are significant differences between freshman and junior (mean difference:0.36) and sophomore and senior (mean difference:0.47) college students on the low mood dimension.

The reason for the differences in the dimension of low mood among physical education college students in different grades is more related to the different problems they face in different grades.

When studying the low mood dimension in different grades, it was found that physical education college students in their junior year faced not only academic pressure but also great mental pressure from job hunting, and thus were relatively the least positive in terms of academic mood problems.

In contrast, sophomore physical education majors have experienced the wear and tear of freshman year, and their interest in academics has decreased, resulting in a lower sense of emotional depression among sophomore physical education majors compared to freshman students.

Finally, senior students have less academic pressure and basically determine the direction of employment or further study.

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Table 7 Comparison of grade level differences on the dimensions of learning burnout

Dimensionality	Learning Burnout	Depressed mood	Inappropriate behavior	Low sense of accomplishment
Freshman year (n=144) M±SD	2.61±0.54	2.63±0.78	2.78±0.68	2.51±0.74
Sophomore year (n=160) M±SD	2.71±0.41	2.71±0.68	2.92±0.58	2.48±0.56
Junior year (n=148) M±SD	2.94±0.58	2.94±0.68	3.06±0.71	2.62±0.68
Senior year (n=164) M±SD	2.61±0.41	2.58±0.75	2.66±0.62	2.85±0.53
F	2.242	2.864	2.154	0.631
P	P>0.05	P<0.05	P>0.05	P>0.05
Multiple post hoc comparisons	3>1		3>4	

Table 8: Multiple comparisons of LSD on the low mood dimension across grades

Grade(M)	Grade(M)	Mean Difference	P
Freshman year(2.65)	Sophomore(2.74)	0.14	P>0.05
	Junior(2.96)	0.36	P<0.05
	Senior(2.57)	0.05	P>0.05
Sophomore year(2.74)	Junior(2.57)	0.21	P>0.05
	Senior(2.58)	0.25	P>0.05
Junior year(2.94)	Senior(2.52)	0.47	P<0.05

Urban-rural differences in learning burnout among physical education college students in Liaoning Province

In order to make a better study and judgment of students' burnout, the influence of physical education college students' home location on their burnout was studied. The FS-mMc method of maximum information entropy model was used to compare and analyze the influence of urban-rural differences on the learning burnout of physical education college students, and the results are shown in Table 9.

The word study burnout among physical education college students is associated with urban-rural differences. Analysis of the data in the table shows that there is no significant difference between physical education majors' universities with different home locations on learning burnout in the dimension of low mood (P>0.05) and in the dimension of inappropriate behavior (P>0.05). In

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contrast, there was a significant difference between urban and rural differences in the effect of learning burnout on the dimension of low achievement (P<0.05). With respect to the data obtained, it seems that the effect of rural-urban differences on burnout was not significant in the dimension of low mood (rural:2.7, urban:2.63, mean difference:0.06, p>0.05) and in the dimension of inappropriate behavior (rural:2.96, urban:2.87, mean difference:0.17, p>0.05), thus indicating that physical education majors.

This indicates that the main causes of burnout among physical education majors are not in the emotional depression and inappropriate behavior dimensions of burnout. However, there is a significant difference between rural and urban areas in the low achievement dimension of learning burnout (rural area: 2.67, urban area: 2.45, mean difference: 0.26, p<0.05), therefore, it can be inferred that the main reason for the development of learning burnout among physical education majors is the low achievement dimension of learning burnout, which is influenced by the urban-rural difference. The main reason for this phenomenon is the low achievement dimension of learning burnout. This phenomenon may be due to the fact that urban life is richer than rural life and urban college students have higher demands on themselves, so that their sense of achievement is lower compared to rural college students.

Table 9: Comparison of urban-rural differences across dimensions

Dimensionality	Rural (n=3655) M±SD	City (n=3655) M±SD	Mean Difference	T	P
Study Burnout	2.71±0.47	2.66±0.54	0.13	1.638	P>0.05
Depressed mood	2.7±0.73	2.63±0.68	0.12	0.674	P>0.05
Inappropriate behavior	2.96±0.62	2.87±0.67	0.17	0.894	P>0.05
Low sense of accomplishment	2.67±0.68	2.45±0.57	0.20	2.214	P<0.05

Conclusion

In this paper, we propose a maximum information entropy model based on the information entropy model of fuzzy rough sets, use this model to calculate and analyze various data generated by students, discover the factors that affect students' learning, and finally optimize physical education for better management of students by addressing the influencing factors.

For model capability testing, this paper uses 12 datasets from the UCI database to test the model and compares the results with the CFS, Re-lief and InfoGain algorithms. The model in this paper performs more consistently and has the highest classification accuracy on nearly half of the datasets, and obtains the highest average classification accuracy under C4.5, Bagging and NaiveBayes conditions. For Cle, FS-mMC improves the accuracy by 16.42% over other algorithms with at least half the number of selected features. For the Lc dataset, this model improves the accuracy by 8.97% with nearly half of the number of features in the subset. Therefore, this algorithm is stable and effective.

After analyzing the factors influencing the formation of students' learning burnout situation, it was found that physical education college students were mainly influenced by gender, grade, and urban-rural differences factors in learning burnout. Under the gender difference, female college students' sense of achievement was higher than male college students. Under the grade difference, the problem of low mood was the most severe for junior college students, followed by junior college students, freshman college students, and senior college students, and the problem of low mood was relatively the least severe. In terms of urban-rural differences, intra-urban physical education college students have a lower sense of achievement than rural college students.

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References

Akiyama, T. (2020). Undokai and sports events in the Japanese school system. *Pediatrics International, 62*(11), 1230-1233.
Beale, N., Eldridge, E., Delextrat, A., Esser, P., Bushnell, O., Curtis, E., . . . Dawes, H. (2021). Exploring activity levels in physical education lessons in the UK: a cross-sectional examination of activity types and fitness levels. *BMJ Open Sport & Exercise Medicine, 7*(1), e000924.
Dong Z, W. W. (2016). Study on the Training Mode in Customized Education of Sports Talent. *Shanxi Science and Technology*.
Druz, V., Iermakov, S., Artemyeva, G., Puhach, Y., & Muszkieta, R. (2017). INDIVIDUALIZATION FACTORS OF STUDENTS'PHYSICAL EDUCATION AT MODERN STAGE OF ITS REALIZATION. *Physical education of students, 21*(1), 10-16.
E., Y.-M. H. (2016). The Research of Development Evolution of Physical Education Curriculum in America Schools. *Journal of Guangzhou Sport University*.
Erfle, S. E., & Gamble, A. (2015). Effects of daily physical education on physical fitness and weight status in middle school adolescents. *Journal of School Health, 85*(1), 27-35.
Gao J, U. B. F. (2019). The Application of Modern Education Technology in College Physical Education Teaching. *Bulletin of Sport Science & Technology*.

Kubai, J. T., Mwangi, P. W., & Owiti, B. (2021). University Education Academic Policies and Students' Sports Talent Development:: Pre-Competency Based Curriculum (CBC) Implementation in the University Education in Kenya. *International Journal of Professional Practice, 9*(2), 32-43.

Lin, W. (2021). Innovative Thinking in Higher Vocational Colleges' Physical Education. *Journal of Contemporary Educational Research, 5*(6), 14-18.

Martínez-Santos, R., Founaud, M. P., Aracama, A., & Oiarbide, A. (2020). Sports teaching, traditional games, and understanding in physical education: A tale of two stories. *Frontiers in Psychology, 11*, 581721.

Minin M. G, F. E. O., Minich A. S, et al. (2020). Export of Higher Education: Innovations in Physical Education Practice. *Vysshee Obrazovanie v Rossii = Higher Education in Russia, , 29*(6), 129-135.

Oliiar, M., Havryliuk, M., Antonenko, T., Lopatenko, Y., & Tymofieieva, I. (2020). Improving Educational Policy in the Context of Improving the Organizational Structure of Physical Education Lessons in Schools.

Richards, K. A. R. (2015). Role socialization theory: The sociopolitical realities of teaching physical education. *European Physical Education Review, 21*(3), 379-393.

Wang J Y, W. B., Huang A. F. . (2010). Comparison of the contents of school physical education teaching method related textbooks used in China and the United States. *Journal of Physical Education*.

Yang, S., & Li, T. (2018). College physical education reform research on the cultivation of university students' physical education lifestyle [J]. *Heilongjiang Science*.

Мосійчук, Л. (2020). Modern principles of implementation of personal-activity approach to physical education of students. *Науковий часопис Національного педагогічного університету імені МП Драгоманова. Серія 15. Науково-педагогічні проблеми фізичної культури (фізична культура і спорт)*(8 (128)), 124-128.