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Using Bayesian network modeling to analyze the link between students' psychological changes and athletic performance in physical education

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Abstract The relationship between students' psychological changes and athletic performance in physical education has an important impact on teaching quality. Traditional research methods are difficult to accurately portray this complex nonlinear relationship. In this study, a Bayesian network model was constructed based on the improved MMHC algorithm to analyze the association between students' psychological changes and sports performance in physical education. A stratified whole group sampling method was used to collect data from 2,480 students from 32 high schools in 16 cities in Shandong Province, using the Canadian Assessment of Physical Literacy Questionnaire (CAPL-2) and the Symptom Self-Rating Scale (ACL-90). The traditional Bayesian network was optimized by the event extraction algorithm with the improved MMHC algorithm to establish a network topology containing 17 measures. The results showed that the model prediction accuracy reached 90.37%, and the number of days of participation in moderate- and high-intensity activities in a week had the greatest impact on the mental health level, with a decrease of 9%. Sensitivity analysis showed that four factors, including the definition of health, safe behavior in performing physical activity, the correct way to improve motor function, and the time required to perform physical activity daily, were the sensitivity factors. The study reveals the causal chain of motivation and confidence → knowledge and understanding → daily behavior → mental health level, which provides theoretical support for the reform of physical education.

Index Terms Bayesian network, physical education, mental health, sports performance, MMHC algorithm, sensitivity analysis

I. Introduction

Physical education is a compulsory course of study that allows students to learn knowledge, skills and methods of physical education and health through physical practice to enhance physical and mental health [1]. Physical education teachers' teaching design, methods and content will largely determine students' interest and motivation in physical education learning and affect the quality and progress of physical education teaching [2]. Students will have a variety of different psychological activities that will affect their behavior in the process of physical education learning [3], [4]. Positive psychology will have a positive impact on students' physical education learning behavior and promote students to actively participate in physical education activities, thus improving the quality of physical education teaching in colleges and universities [5]. And if students have a negative sport learning psychology, it will affect their interest and motivation in sport learning, hinder their learning and progress in sport teaching, and also hinder the implementation and development of sport teaching [6], [7].

Sport psychology is an important part of the discipline of psychology, with the main purpose of improving the effectiveness of sports teaching and learning, the theoretical content involves the psychological activities, behavioral motives and related psychological laws and other relevant content that exist in students during sports activities [8]-[10]. Compared with sport psychology and exercise psychology, sport psychology theory and practice is more suitable for physical education teaching, aiming to improve the effect of physical education teaching, the target is mainly for students and physical education teachers [11]. When students produce negative negative psychological activities, if physical education teachers can understand and take relevant measures in time through the relevant knowledge of sport psychology, this can have a positive impact on both the implementation of physical education teaching and the cultivation of students' sports performance [12], [13].

In physical education, there can be great differences in students' athletic ability [14]. To investigate the root cause, I think that in addition to the differences in students' physical quality, their psychological factors are also an important reason. Psychological factors are the movement, changing mental processes, students' psychological factors include attention state, emotional state, will state and so on [15], [16]. The positive or negative tendency of these psychological factors largely affects the students' athletic performance, thus causing differences [17]. It can be seen that paying attention to the psychological changes of students in physical education can effectively promote the overall development of students and improve the quality of physical education teaching [18]. Bayesian network is a product of the integration of graph theory and probability theory, is a kind of graphical model that can carry out probabilistic reasoning, which uses directed acyclic graphs to represent probabilistic relationships [19]. Bayesian networks not only use graph theory to visualize the structural relationships between problems, but also follow the principles of probability theory and the use of Bayesian network structure to reduce the complexity of network inference [20], [21]. Therefore, Bayesian networks are widely used in modeling complex systems. It is of great significance to use Bayesian network modeling method to study the complex connection between students' psychological changes and sports performance in physical education.

As an important part of school education, physical education plays an irreplaceable role in promoting students' physical and mental health. Students' psychological state directly affects their athletic performance, while athletic participation in turn acts on psychological health, and there is a complex interaction between the two. In recent years, educators have paid more and more attention to the study of students' psychological factors in physical education, but traditional linear analysis methods are difficult to fully reveal this multivariate, nonlinear and complex relationship. Bayesian network, as a modeling method integrating probability theory and graph theory, can effectively deal with uncertainty information and describe the conditional dependence relationship between variables, showing unique advantages in the field of education research. Through structural and parametric learning of Bayesian networks, key factors affecting students' mental health can be identified, causal relationships between variables can be found, and quantitative support for educational decision-making can be provided. Aiming at the methodological limitations existing in the current research on physical education, this study proposes a Bayesian network model based on the improved MMHC algorithm, combined with the event extraction technique, to construct a multidimensional index system for physical literacy. Through a large-scale survey of high school students in several cities in Shandong Province, data on dimensions such as daily behavior, knowledge and understanding, motivation and confidence were collected, and machine learning methods were used to mine the potential patterns in the data. The study not only focuses on the influence of single factors on mental health, but also pays more attention to the interaction and conduction paths among the factors, and identifies the key control points through sensitivity analysis to provide precise guidance for physical education teaching practice.

II. Improved MMHC-based Bayesian network modeling

In this chapter, the traditional Bayesian network model is improved by using the event extraction algorithm and the improved Maximum Minimum Hill Climbing Algorithm, and the Bayesian network model based on the improved MMHC is constructed, which provides theoretical support for the correlation analysis of the students' psychological changes and athletic performance in physical education teaching.

II. A.Principles of Bayesian Networks

Bayesian networks are a combination of probability theory and graph theory and consist of two parts, a directed acyclic graph consisting of nodes representing variables and directed edges connecting these nodes, and a conditional probability table for the given data, which determines the strength of the relationship between the variables [22]. For a joint probability distribution with n nodes $(x_1, x_2, \cdots, x_n)$ is represented as:

$$P(x_1, x_2, \cdots, x_n) = \prod_{i=1}^{n} P(x_i \mid parent(x_i)) \tag{1}$$

where: $P\left(x_i \mid parent(x_i)\right)$ is the local conditional probability distribution associated with node i, and $parent(x_i)$ is the parent of the labeled node i (if node i has no parent, $parent(x_i)$ can be null).

Bayesian network modeling consists of two steps: structure learning and parameter learning.

II. A. 1) Structural learning

Bayesian network structure learning means determining the directed acyclic graph (DAG) of the Bayesian network. Considering the large number of variables and the complexity of the model in this experiment, in order to improve the accuracy of the Bayesian network model, a priori knowledge will be integrated to learn the structure of the Bayesian network. The final variable interrelationships determined based on prior knowledge are:

$$[(\Delta V_x, \varphi); (\Delta V_y, \varphi); (a_B, \varphi); (a_C, \varphi)] \in \delta_e \tag{2}$$

$$\begin{bmatrix}(\omega,\varphi);(X_{BC},\varphi);(Y_{BC},\varphi);(a_B,\Delta V_x);\\(a_C,\Delta V_x);(\Delta V_{AB},L_{AB});(\Delta V_{CD},L_{CD})\end{bmatrix}\in\delta_a \tag{3}$$

The interpretation of δ_e,δ_a is as follows: $(x,y)\in\delta_e$ means that the structure $x\to y$ always exists in the network structure during the process of search and learning; and $(x,y)\in\delta_a$ means that $x\to y$ or $y\to x$ always exists during the process of search and learning.

II. A. 2) Parameter learning

After determining the structure of the Bayesian network, it is necessary to carry out parameter learning for the Bayesian network, which is essentially to obtain the conditional probability table (CPT) of each node under the condition that the structure of the network is known. The dataset collected this time is a perfect dataset with no missing data, and the method of maximum likelihood estimation is used for parameter learning.

II. A. 3) Reliability verification

In order to verify the adaptability of the trained Bayesian network for different scenarios, this paper introduces the K-Fold cross-validation to validate the Bayesian network obtained by machine learning. This validation method can evaluate the generalization ability of the model, i.e., test the applicability of the trained Bayesian network to various different traffic scenarios. The Bayesian network is validated using the cross-validation approach to verify the accuracy and reliability of the model's conflict-free recognition.

II. B. Causal event extraction

Combined with the definition of event extraction tasks in ACE, this paper defines the scope of causal event extraction tasks. The three subtasks of causal event extraction include event trigger word extraction, event parameter extraction, and causal event classification.

The accident symptom narrative text is the input data of the causal extraction algorithm, and its syntactic structure is more complex, which increases the difficulty of semantic extraction. In order to improve the accuracy and efficiency of the algorithm, this paper calls Stanford Parser to parse the dependencies of semantic components in the accident description text and simplify the narrative text. For the trigger word t in the statement, the event semantic structure S_t can be constructed based on the event parameters and parameter relationships. For an existing causative event type e, its event type is taken as the root and the semantic structure S_e containing its predefined parameters is constructed.

By Bert word embedding, the relationship of parameters w_1, w_2 in the event semantic structure S_t of the statement is shown in equation (4):

$$V_t=\left[V_{w_1};V_{w_2}\right]\times M_\varphi \tag{4}$$

where w_1,w_2 are semantic structural parameters; V_{w_1},V_{w_2} are d-dimensional vectorized representations of the parameters w_1,w_2; M_φ is the matrixed representation of the parameter relations; and V_t is the vectorized representation of the parameters w_1,w_2 and their relationships.

The predefined causal event type, S_e, is similarly vectorized as V_e. The output of Bert is the input of the classification model, which calculates the similarity between the input events and the event types, and outputs the event type with the highest similarity as the result of event extraction as shown in equation (5):

$$V_{e^*}=\arg\max_{e_i\in E}\frac{V_t\times V_{e_i}}{\|V_t\|\|V_{e_i}\|} \tag{5}$$

where, e^* is the event type with the highest similarity of statement t; V_{e^*} is the vectorized representation of event type e^*; E is the set of event types; e_i is the event type in E; and V_{e_i} is the vectorized representation of e_i.

II. C. CAPTI-BN Network Learning

In this paper, we propose an improved MMHC algorithm by using CAPTI-BN node definitions, predefining some of the relationships between nodes, and combining the classical max-min hill-climbing algorithm in hybrid algorithms [23]. The specific execution steps of the algorithm are as follows:

Step 1: Determine the blacklist and whitelist. Blacklist refers to the set of node pairs that do not have causal relationship. Whitelist refers to the set of node pairs where causal relationship exists.

Step 2: Forward Process. Based on the CPC and its subsets, get all the variables except the variables within the CPC associated with the T minimum condition and take the maximum value of it, and the variable F that reaches the maximum value, as shown in Eqs. (6)~(7):

$$assocF = \max_{x\in V} Minassoc(X;T \mid CPC) \tag{6}$$

$$F = \arg\max Minassoc(X;T \mid CPC) \tag{7}$$

where, V is the set of variables X; T is the target variable; CPC is the set of candidate parent-child nodes of variable T; $assoc(X;T \mid CPC)$ is the CPC conditional association function of variable X with T; $assocF$ is the conditional association maximum; F is the value of X when the conditional association takes the maximum.

.The association value function $assoc(X;T \mid CPC)$ is measured by the G^2 statistic. The p value corresponding to the G^2 statistic is computed and taken to be negative as the result of the association value function. Usually X and T are conditionally independent for p values below 0.05. If F and T are not conditionally independent, the variable F is added to the CPC, and the above process is repeated until the set of CPCs is no longer changing, as shown in Eqs. (8)~(9):

$$G^2(X;T \mid CPC) = 2\sum_{a,b,c} S^{abc}_{X,T,CPC} \ln \frac{S^{abc}_{X,T,CPC} S^{abc}_{CPC}}{S^{ac}_{X,CPC} S^{bc}_{T,CPC}} \tag{8}$$

$$assoc(X;T \mid CPC) = -p - value(G^2) \tag{9}$$

where a, b, c are the values of variables X, T and the set of CPCs, respectively; $S^{abc}_{X,T,CPC}$ is the number of times $X = a$, $T = b$, $CPC = c$ occurs in the dataset; S^{abc}_{CPC} is the number of times $CPC = c$ occurs in the dataset; $S^{ac}_{X,CPC}$ is the number of times $X = a$, $CPC = c$ occurs in the data set; $S^{bc}_{T,CPC}$ is the number of times $T = b$, $CPC = c$ occurs in the data set.

Step 3: Backward process. After traversing all the variables in CPC, output the parent and child nodes whose variables T satisfy the condition independent to get the new CPC table.

Step 4: Mountain Climbing Algorithm [24]. The greedy hill-climbing algorithm is applied to add new arcs, delete existing arcs, and change the direction of arcs to the network structure. Where new arcs $A \to B$ are added when and only when A belongs to the CPC set of B and $A \to B$ does not belong to the blacklisted set, and finally, the network structure with the highest BDeu score is outputted.The BDeu scoring function assumes that the model satisfies the Dirichlet distribution, and the computational process is shown in equations (10)~(11):

$$f_{BDeu}(G,D) = \sum_{i=1}^{n}\sum_{j=1}^{q_i}\left(\log\frac{\Gamma\left(\frac{m'}{q_i}\right)}{\Gamma\left(\sum m_{ijk} + \frac{m'}{q_i}\right)} \sum_{k=1}^{r_i} \log\frac{\Gamma\left(m_{ijk} + \frac{m'}{r_i q_i}\right)}{\Gamma\left(\frac{m'}{r_i q_i}\right)}\right) + \log P(G) \tag{10}$$

$$m' = \frac{1}{r_i q_i \alpha_{ijk}} \tag{11}$$

where G is the network structure; D is the dataset; $f_{BDeu}(G,D)$ is the BDeu scoring result of the network structure G in the dataset D; Γ is the Gamma function; n is the number of nodes; m_{ijk} is the number of samples when the state of node i is k and the parent node takes the value j; r_i is the number of states of node i; q_i is the number of combinations of values taken by the parent node; α_{ijk} is the Dirichlet distribution parameter; m' is the intermediate statistic; and $P(G)$ is the probability distribution of G.

In the parameter learning stage, the conditional probability table (CPT) for each node is computed in conjunction with the parent-child node distribution of structural learning.

III. Analysis of the correlation between psychological changes and athletic performance in physical education students

In this chapter, an in-depth study and research on the exercise between students' psychological changes and sports performance in physical education will be conducted in conjunction with the Bayesian network model based on the improved MMHC proposed in this paper.

III. A. Study population and data sources

III. A. 1) Subject of the study

The target population of this study was selected from Shandong Province, China, which is a major education province in China, and the study of the association between psychological changes and athletic performance of physical education students will be of great significance to other provinces. In order to ensure the comprehensiveness of the survey sample, according to the principle of stratified cluster sampling, one district and one county were randomly selected from each of the 16 cities in Shandong Province, one high school was selected from each district (county), and two first-grade classes were randomly selected from each school, with an effective sample of not less than 70 students. 2480 subjects were selected from 32 elementary school, and all of them were healthy and did not have any motor dysfunction.

III. A. 2) Research data sources

In this study, the Canadian Assessment of Physical Literacy Questionnaire (CAPL-2) and the Autocompassionate Rating of Symptoms Scale (ACL-90) will be used to assess the physical literacy and mental health of the surveyed students. In this study, 2480 questionnaires were finally collected, with a 100% recovery rate, 2107 valid questionnaires, and a validity rate of 84.96%.

III. B. Research variables

The independent and control variables used in this study are specifically shown in Table 1. The dependent variable was the students' mental health level, and the independent variables were from the Canadian Assessment of Physical Literacy Questionnaire (CAPL-2), which includes three of the four dimensions of physical literacy except for the mental health level, namely, daily behavior, knowledge and understanding, and motivation and confidence. These three dimensions are divided into 17 measures.

Table 1: Research variable

Type of variable	Variable name
Dependent variable	Fitness level
Independent variable	Average daily activity time (B1)
	Sedentary time (B2)
	Days of participating in moderate and high intensity activities within a week (B3)
	Understanding of physical activity (C1)
	Time required for daily physical activity (C2)
	Maximum time to face an electronic screen (C3)
	Understanding of Cardiopulmonary Health (C4)
	Understanding of muscle strength and endurance (C5)
	Definition of health (C6)
	Safe conduct of physical activity (C7)
	Correct ways to improve motor function (C8)
	The correct way to get a good body shape (C9)
	Dynamic and static activity preferences (C10)
	Compared with their peers, the degree of love for sports activities (D1)
	Evaluation of self-exercise level compared with peers (D2)
	Reasons for liking / disliking sports (D3)
	Internal motivation of physical activity (D4)

III. C. Bayesian network modeling

In this study, GeNIe2.3 software was applied, and a combination of expert knowledge and machine learning was used for structural learning to construct a Bayesian network topology of the factors influencing the mental health level in physical literacy, as shown in Figure 1. The model shows the network structure of the factors affecting the mental health level and the conditional probability table of each node.

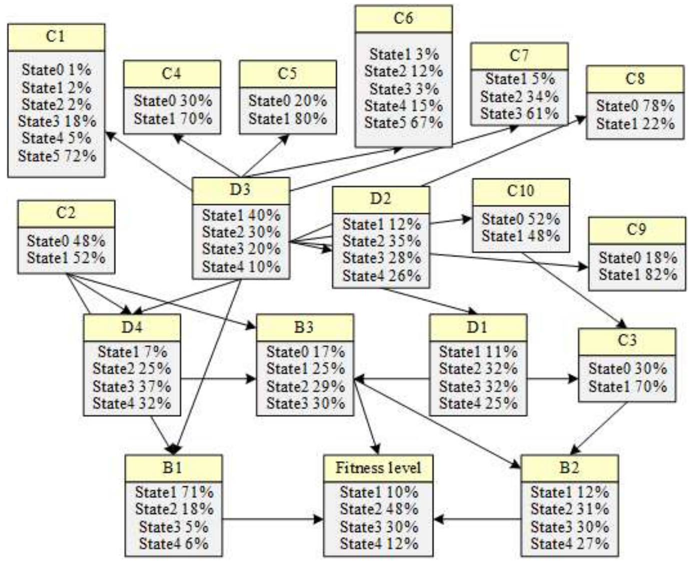

Figure 1: Bayesian network model

III. D. Bayesian network test

The reasonableness and validity of the model structure must be ensured before performing probabilistic inference analysis and sensitivity analysis on the constructed Bayesian network model. In this section, the inference results of the model are compared with the actual results using the research data as a judgment of model validity.

Before the test, because the Bayesian network inference results for the corresponding risk occurrence of the level of probability, so we need to divide the probability and the level of the corresponding situation, the division of the program is shown in Table 2. The scoring results of the mental health level in the original data are discretized, and the discretized results are also one, two, three and four grades, and the larger the value is, the higher the corresponding risk is.

Table 2: Risk level

Risk level	Risk results	Risk probability
Level I	High risk	75%~100%
Level II	High risk	50%~75%
Level III	General risk	25%~50%
Level IV	Low risk	0%~25%

The research data in accordance with the ratio of 7:3 divided into training set and test set data, selected 135 groups of data for testing and verification, and each node of the defuzzification data input, judgment test results and the actual results of the accuracy of the test results and the actual results of the model validity test basis don't on the Bayesian network model prediction results and the data in the record of the consistency of the analysis, to obtain the confusion matrix is shown in Figure 2. The values on the diagonal line are the number of cases in which the predicted values of the model are the same as the actual values in the test set, and the values on the off-diagonal line are the number of cases in which the predicted values are different from the actual values. According to the results shown in the confusion matrix, out of 135 groups of cases, 122 groups of risk level test results using the model are the same as the actual values, and the model achieves a prediction accuracy of 90.37%.

III. E. Analysis of probabilistic inference for Bayesian networks

1) Analysis of important factors affecting mental health level

The parameter of the target node “mental health level” is set to 100% probability of “State4”. Then it can show the change of the probability of each node when the mental health level is excellent, and the inference results are shown in Figure 3. Compared with the initial Bayesian network model, the probability of most of the indicators at the good level increases to different degrees, the probability of the poor level decreases to different degrees, and the probability of some indicators does not change.

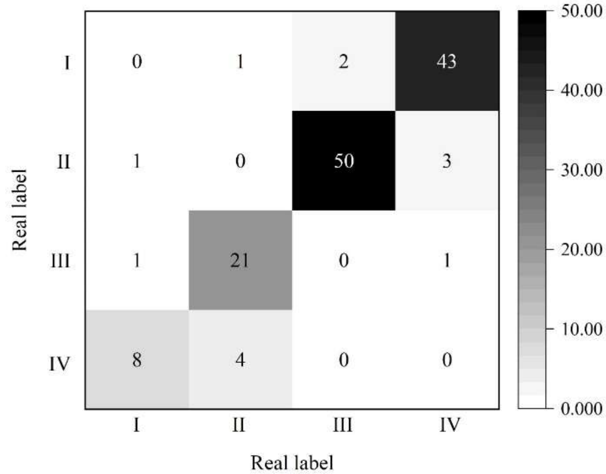

Figure 2: Confusion matrix

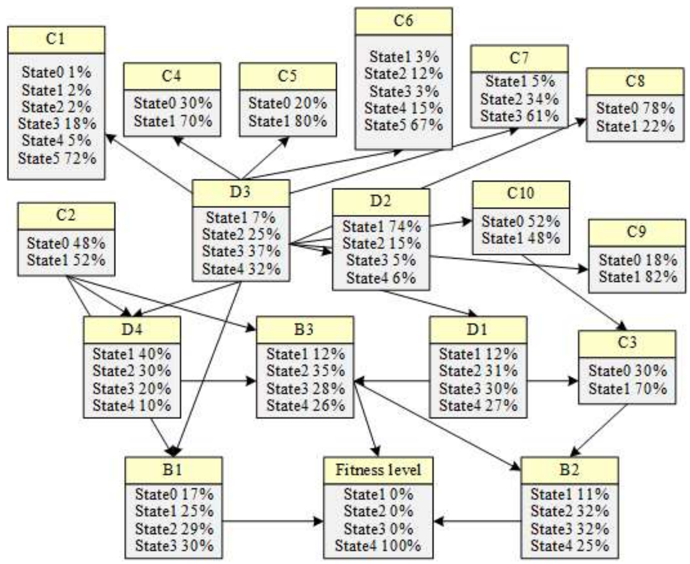

Figure 3: The result graph of reverse reasoning in State4 100 %

In order to compare more clearly which indicator has a greater impact on fitness levels, the probability of failing mental health (State1) was set to 100% and the results of the run are shown in Figure 4. In contrast to the “State4” probability of 100%, when mental fitness level drops from excellent to failing, an analysis of the change in each indicator clearly reveals that the largest decrease is in the number of days of participation in moderate to vigorous activity in a week (B3), which drops by 9%, indicating that the number of days of participation in moderate to vigorous activity in a week is the the factor with the greatest impact on fitness levels. The same analysis shows that the sequentially important influencing factors are sedentary time (B2), the time required to perform physical activity per day (C2), the level of love for physical activity compared to peers (D1), and internal motivation for physical activity (D4).

2) Causal chain analysis of influencing mental health level

The width of the directed line segments between nodes in GeNIe2.3 can indicate the strength of the influence between two nodes, if several nodes are connected by wider line segments to form a causal chain and point to the target node, it means that this causal chain has a greater influence on the promotion of physical fitness level, as shown in Figure 5. As can be seen from the figure, when the mental health level is excellent, five causal chains pointing to the target node with a greater intensity of influence appear, for example, reasons for liking/disliking exercise (D3) → time required for daily physical activity (C2) → number of days of participation in medium- and high-intensity activities in a week (B3) → fitness level; reasons for liking/disliking exercise (D3) → internal motivation for physical activity (D4) → Number of days of participation in moderate to high intensity activities in a week (B3) → mental fitness level. Overall, the causal chain can be summarized as Motivation and Confidence →

Knowledge and Understanding → Daily Behavior → Physical Fitness Level. Positive motivation and participation in sports are the main causes of positive daily behavior, and making young people enjoy sports activities and participate in them is the fundamental way to improve students' physical literacy and mental health.

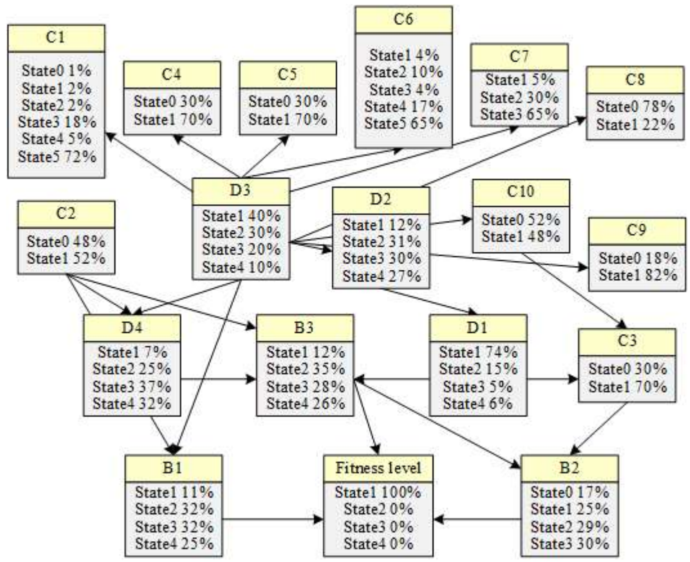

Figure 4: The result graph of reverse reasoning in State1 100 %

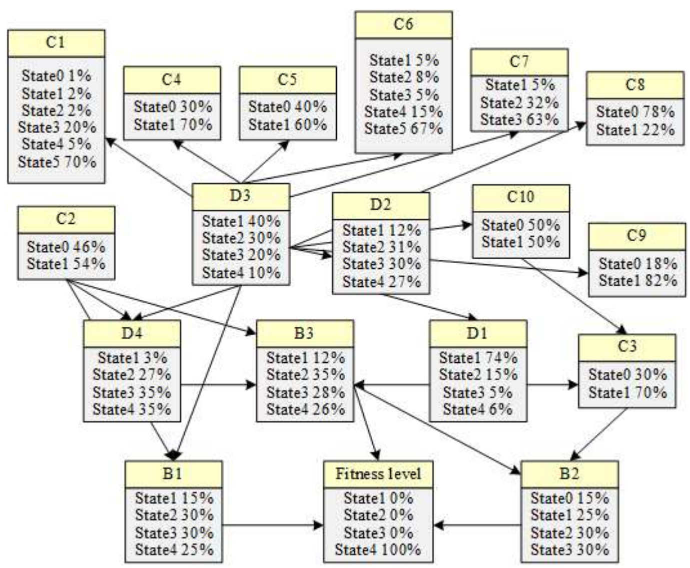

Figure 5: Impact strength analysis

III. F. Bayesian network sensitivity analysis

Taking "mental health level" as the target node, the sensitivity indexes of REV and AVG of each node of the Bayesian network are calculated, and the results are shown in Figure 6. The larger the value of AVG index, the higher the sensitivity of the factor. As can be seen from the figure, the relatively high sensitivity of the indicators of the definition of health (C6), safe conduct of physical activity behavior (C7), the correct way to improve motor function (C8), and the time required for daily physical activity (C2) are called sensitivity factors, that is to say, small changes in these factors can also have a significant impact on the level of students' mental health, for example, students are unable to improve the effectiveness of the motor function, not following safety principles in physical activities, etc. can affect the level of mental health of students. The factors are summarized:

1) Sensitivity factors. Through sensitivity analysis, four sensitive factors were identified as the definition of health (C6), safe physical activity behaviors (C7), the correct way to improve motor function (C8), and the time required for daily physical activity (C2), which should also be highly valued and strictly controlled by schools and teachers.

2) General factors. The 13 factors other than the sensitive factors are called general factors, which have been controlled well and should be maintained.

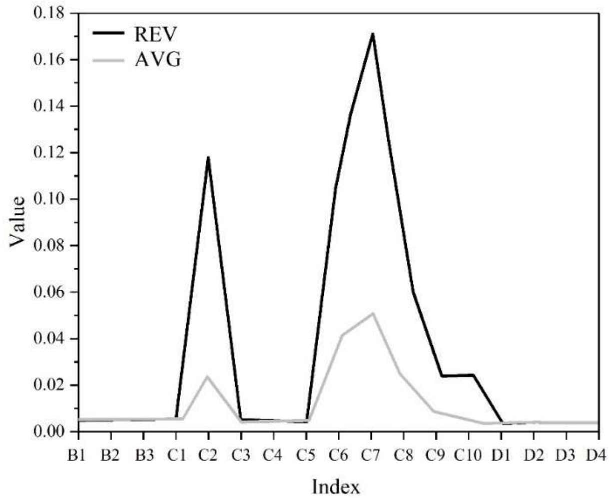

Figure 6: Sensitivity analysis results

IV. Conclusion

By constructing a Bayesian network model based on the improved MMHC algorithm, the influence mechanism of students' mental health level in physical education was deeply revealed. It was found that the number of days of participation in medium- and high-intensity activities in a week was the most important influencing factor, and when the level of mental health was reduced from excellent to failing, this indicator decreased by 9%, which was significantly higher than other factors. Factors such as sedentary time, daily time spent performing physical activity requirements, and love of physical activity compared to peers also showed strong correlations. Sensitivity analyses identified four key sensitivities, with the definition of health having the highest sensitivity, suggesting that changes at the cognitive level can have a significant impact on mental health. The discovery of the five main causal chains provides a clear pathway for intervention in educational practice, particularly motivation and confidence as source factors that ultimately influence mental health levels through the mediating role of knowledge understanding and daily behavior. Based on the 90.37% model prediction accuracy, it is recommended that educators focus on the development of students' motivation to participate in sports and optimize the time schedule of physical activities, as well as strengthen the education of health knowledge and the cultivation of safety awareness, so as to effectively improve students' mental health.

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