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Article

Biomechanics of physical exercise: A data-driven approach to enhancing mental health in college students

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Abstract: With growing awareness of the importance of mental health, the biomechanical mechanisms of physical exercise have gained attention as an effective intervention for improving mental well-being, particularly among college students. Physical activity not only enhances physical fitness and disease resistance but also contributes to cognitive and emotional health through specific biomechanical pathways. This study explores the interplay between exercise biomechanics and mental health by investigating the psychological challenges faced by college students. Utilizing advanced data analysis and correlation techniques, we refine the Apriori algorithm through a novel database partitioning strategy, achieving a 23.68% improvement in accuracy and a 10.17% reduction in runtime compared to the baseline. Additionally, this study examines how biomechanical factors, such as joint movement and muscle activity, influence brain function and mental health outcomes. The findings offer innovative perspectives for integrating biomechanical insights into mental health education and exercise-based interventions for college students.

Keywords: biomechanics; physical exercise; mental health; college students; data mining

1. Introduction

Mental health (MH) refers to an individual's positive psychological state and their ability to adapt well to their environment, reflecting the high standards humans pursue for their well-being [1]. Research indicates that individuals who regularly engage in physical exercise (PE) experience significantly lower levels of negative emotions, such as depression and anxiety, compared to those who do not exercise. Conversely, those who participate in PE report higher levels of positive emotions and overall happiness. PE is increasingly recognized not only as a means to improve physical fitness but also as a vital tool for psychological regulation [2,3].

With ongoing reforms in physical education at colleges and universities, there is a growing recognition of the interconnectedness between physical education and the mental health of college students. From the perspectives of educational psychology and mental hygiene, the holistic development of students is closely tied to their mental health. Some studies suggest that PE can enhance academic performance, primarily by improving classroom behavior and increasing student attention [4]. This highlights the need for scientific research on mental health quality to provide theoretical guidance for improving mental health levels and preventing various mental disorders within the Chinese population.

Regular participation in sports activities not only expands social networks but also fosters greater acceptance and provision of social support, making sports a crucial avenue for enhancing social connections [5]. In recent years, as health concerns gain prominence and understanding of psychological phenomena deepens, research on mental health has flourished. Numerous scholars worldwide have sought to define mental health and establish relevant standards, with ongoing debates shaping this field.

A consensus is emerging that physical exercise positively influences mental health, drawing attention from psychologists to the psychological changes that accompany exercise behavior. For instance, Helena et al. [6] argue that, in the modern healthcare landscape, the impacts of mental health and social behavior on the quality of life for middle-aged and elderly individuals often overshadow biological factors. Similarly, McKeon et al. [7] investigated the effects of regular aerobic exercise on the mental health of middle-aged individuals, finding no significant changes in anxiety, tension, or depression following physical activity. Research by Yan et al. [8] on aerobic exercise's influence on female college students revealed that those who regularly engage in exercise have higher self-concept scores compared to sedentary peers.

Pablo et al. [9] conducted a survey of college students' exercise behaviors, finding a concerning lack of guidance and support for fostering healthy habits and promoting exercise effectiveness. Melanie et al. [10] noted that students generally perceive a deficiency in equipment for physical education, with boys identifying a lack of equipment and girls citing insufficient facilities. Ali's [11] investigation found a strong correlation between students' mental health and their participation in sports, with those who engage in physical activity reporting better mental health outcomes and lower levels of anxiety, hostility, and depression. Miranda et al. [12] measured psychological symptoms immediately post-exercise and found significant reductions in anxiety, depression, and other psychological disorders, along with increased feelings of energy and pleasure. Data mining (DM) is a process that employs specific algorithms to analyze large datasets, extracting valuable insights that may not be readily apparent. The integration of DM across various fields, theories, and technologies has expanded beyond artificial intelligence and machine learning to encompass a wide array of applications.

He et al. [13] established a multi-dimensional association rule mining model to analyze the correlation between six information attributes and nine dimensions of students' psychological symptoms, such as gender and birth order. Sun et al. [14] utilized decision tree (DT) algorithms and Apriori association rule algorithms to mine student psychological data, revealing hidden relationships between psychological symptoms and attributes. Xia et al. [15] examined the correlation among nine dimensions of psychological symptoms and employed the ID3 algorithm to derive classification rules for obsessive-compulsive symptoms based on six pre-selected attributes. Zheng et al. [16] explored the application of DM technologies to college students' mental health, seeking new methods for the early prevention and intervention of mental disorders. Fei and Tian [17] developed a mental health evaluation model using the C4.5 algorithm and decision trees to predict mental health outcomes based on extracted rules.

Wood applied a tree mining algorithm, IMB3-Miner, to derive knowledge from semi-structured patient records, investigating the influences of genetic and environmental factors on mental health issues, thereby providing insights for the prevention and treatment of mental disorders [18]. Jorge et al. [19] improved the

Apriori association rule algorithm in DM technology and applied it to analyze psychological correlations among college students. Xue et al. [20] presented experimental results obtained through the Apriori algorithm to conduct nine-dimensional factor psychological symptom analysis and provided interpretations of these results.

Team sports, which require cooperation among participants, play a significant role in building trust and intimacy while also helping students balance competition and collaboration. Addressing mental health issues is crucial for college students, as these challenges can significantly impact their academic performance and overall life experience. Current research indicates that the effect of PE on mental health is influenced by various factors. This paper utilizes diverse data and correlation analysis techniques to explore the optimal PE strategies for promoting mental health among college students, offering tailored exercise recommendations based on gender and personal preferences.

2. Research method

2.1. Analysis of correlation between college students' PE and psychology

When college students are in a complicated environment, there are often some bad emotions, such as anxiety, depression and depression. PE can help college students get rid of these bad emotions. Thereby controlling people's emotions and improving their MH. The level of negative psychological variables, such as state anxiety, depression, tension and psychological disorder, of those who regularly take part in PE is obviously lower than that of those who do not take part in PE, while the level of positive psychological variables, such as happiness, is obviously higher. PE breaks this kind of closure. It can enable students to have equal, friendly and harmonious communication on the playground, so that people can have a sense of trust with each other, effectively communicate emotions and information, and improve students' interpersonal communication and social adaptability.

College students' participation in physical education (PE) is primarily based on formal PE classes, which serve as a key avenue for interpersonal communication. Whether in team or individual sports, students require mutual cooperation, fostering essential social skills. For many college students, sports are viewed as a form of entertainment. However, given the rise of digital entertainment like mobile phones and online games, many students may overlook the importance of PE. To address this, schools should innovate physical education programs to cultivate students' interest in sports and encourage more active participation.

Data mining (DM) has become an important tool for knowledge discovery in the era of big data. Association rule mining allows us to identify and explore relationships within datasets, ultimately enhancing decision-making processes [4].

Students are reaching maturity in both psychological and physiological aspects, and their mental health issues can directly impact their future development. If mental health problems are not addressed during college, they may influence an individual's entire life trajectory. Therefore, establishing a positive outlook on life and values before leaving campus is crucial for success in personal and professional life. By collecting data on "psychological problem information" and "basic personal information," a new dataset can be constructed for mining insights. After the DM operation, the next step is result interpretation and evaluation, which involves extracting the most valuable information to support decision-makers in taking appropriate actions.

Association rules are generally expressed by the expression of Xcontaining Y, where the intersection of X, Y is an empty set, that is, two sets where X, Y has no common set. The following two formulas intuitively represent the two measures of support S and confidence C:

$$S = (X \rightarrow Y) = \frac{\sigma(X \cup Y)}{N} \tag{1}$$

$$C = (X \rightarrow Y) = \frac{\sigma(X \cup Y)}{\sigma_X} \tag{2}$$

The support degree of rule is the probability that the itemsets in the rule appear at the same time, and the confidence degree is the measure of the confidence degree of the rule. Whether the mined rules are useful or not and their certainty are usually expressed by support and confidence.

Classification and prediction are two methods of analyzing data, which can be used to extract models that can describe important data sets or predict future data trends. Classification method is used to predict discrete categories of data objects; Prediction is used to predict the continuous values of data objects. At present, all DM methods require that the current DM research has been greatly improved on the basis of these works, and the classification and prediction technologies with the ability to process large-scale data sets based on external storage have been developed. These technologies combine the ideas of parallel and distributed processing.

Compared with the classification learning method, prediction is to take the values of the category attributes of unknown category data rows or objects, make predictions by using the model obtained by learning, or evaluate the possible attribute values and value intervals of a given sample. Describe the ability of the model obtained by learning to correctly predict the class or value of unknown objects, involving the ability of the model to correctly predict the class label of new or previously unseen data. In the process of DT generation, the selection strategy of test attributes is very important.

Let S be a set of s data samples. In addition, the category attribute can take m different values, corresponding to m different categories $C_i, i \in \{1,2,\cdots,m\}$. Assume that s_i is the number of samples in category C_i; Then the amount of information needed to classify a given data object is:

$$I(s_1, s_2, \cdots, s_m) = -\sum_{i=1}^{m} p_i \, log_2(p_i) \tag{3}$$

where p_i is the probability that any data object belongs to category C_i; It can be calculated by s_i/s. The LOG function is based on 2, because information is coded by bits in information theory.

There are many discrete data in the MH data set processed in this paper, and the attribute values are also relatively small. For example, whether you grew up with your parents, family income and other attributes are discrete data with only two attribute values. With the increase of the number of college students, the requirements of employment units for the quality of college students are further improved, which to some extent requires the theoretical knowledge to be further broadened and deepened. The process of this study is visually represented in **Figure 1**:

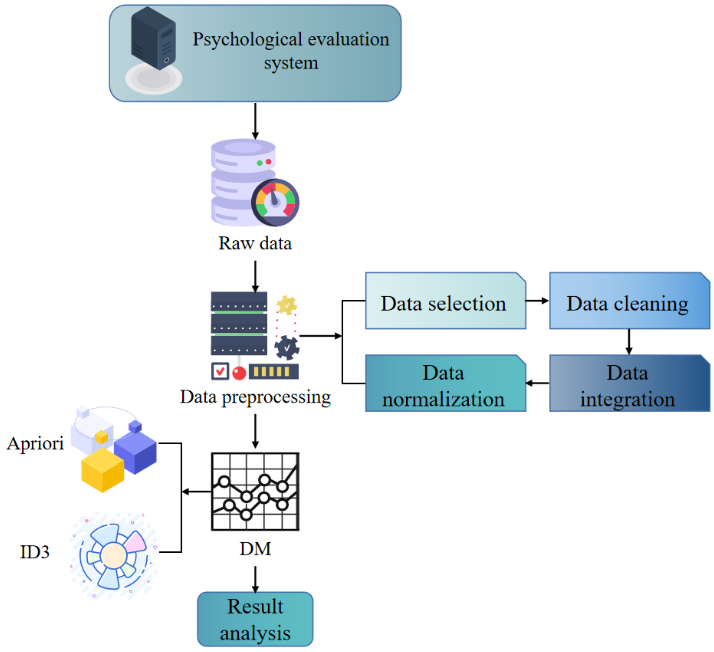

Figure 1. This paper studies the DM architecture process.

The original data is extracted from the psychological evaluation system, and the generation of the original data requires administrators to log in to the system for operation and students to log in to the system for operation. Administrators can add, delete and modify questionnaires, and then the administrators of psychological counseling centers organize students to go to the computer room to fill out forms and improve their personal information, so that the information can be stored in the database of psychological evaluation system.

Association Apriori algorithm is used to mine association rules for each psychological factor in the data table, and DT algorithm in classification is used to mine the implicit relationship between each attribute in basic information of students and psychological symptoms with high occurrence probability, and then the obtained rules are analyzed.

There are 12 factors related to college students' psychological analysis in our data. We can preprocess these data for specific mining needs, so as to improve our mining efficiency and accuracy. We can define x_1 as gender, x_2 as major, x_3 as grade..., then the sample information of a college student is recorded as a 12-dimensional coordinate point, and all data information is the collection of A_i.

$$A_i = (x_1, x_2, \cdots, x_{12}) \tag{4}$$

In this way, we can limit the value range of a certain x_i, so as to conduct relevant mining analysis on other factors after a certain factor is determined.

$$f = \sum_{i} (A_i | x_2 = mj) \tag{5}$$

The purpose of data summary is to condense the data and give its compact description. For example, the traditional and simplest data summary method is the sum and variance of each field in the database. Data synthesis is the generation of new attributes or records, if this is more representative of the original data. Data Merge Combines several data sets together. Data formatting deals with inconsistencies in data.

2.2. Psychological data analysis of college students

At present, many colleges and universities in China only focus on physical education classroom teaching, but pay little attention to students' extracurricular PE. However, students can only learn the most basic physical knowledge and skills in the physical education class. If they want to improve their physical and mental quality, they must take active exercise after class. In teaching, physical education teachers should formulate an assessment task table for college students with weak physique according to their specific conditions, so that they can improve their physical quality step by step. Due to physical reasons, the vast majority of physically disadvantaged college students do not have high enthusiasm to participate in teaching. For college students, physical education classroom teaching is the most direct link that has an impact on them. We should carry out positive psychological intervention in physical education classroom teaching, improve students' understanding of sports and take action for it.

The standard of mental health (MH) is relative, and people's MH is a continuous process. Extreme health represents a state of mental perfection, while extreme challenges represent mental illness, with most individuals falling somewhere between these two extremes. MH is characterized by development and variability. True mental health can only be achieved when individuals continuously improve themselves through various means and experience happiness and satisfaction as a result of their efforts. Quality of life is a multi-dimensional comprehensive measure of the physical, psychological, and social adaptability of individuals or groups, encompassing both objective health status and subjective satisfaction.

By collecting extensive data on college students' MH challenges, an advanced MH intelligent analysis system can be established. This system can alleviate the workload of MH counselors, improve their efficiency, and provide reliable solutions for students experiencing MH problems. In this process, clustering is used to group physical or abstract object sets. The ideal outcome of clustering is to maximize the dissimilarity between clusters while maximizing the similarity within each cluster.

The Apriori algorithm is a classic association rule mining technique that uses support and confidence metrics to identify strong associations. It effectively controls the scale of candidate itemsets and mines association rules that meet specified criteria. The method involves several steps: first, a complete scan is performed to count each candidate itemset, comparing it against the minimum support threshold. Itemsets meeting or exceeding this threshold are retained, while others are eliminated.

In the discernibility matrix, some attribute items with only one attribute may appear. Obviously, this unique attribute must be an essential attribute in reduction, otherwise it will contradict that reduction is the smallest attribute set that can distinguish all objects. Based on this, we propose the following formula:

$$SIG(a) = \sum_{m=2}^{n} (counter_a/m) \tag{6}$$

where n is the number of attributes of the attribute item with the largest number of attributes among all attribute items with a attributes, m is the number of attributes of the attribute item with a attributes, and $counter_a$ is the total number of times that a attributes appear in the discernibility matrix.

In order to establish the correlation matrix, a new table should be built to accommodate one row and each data column of the original data table, and then the calculated correlation should be written into the table to obtain the correlation values of each column with other columns. The formula for calculating correlation is as follows:

$$r = \frac{1}{n-1}\sum_{i}\left(\frac{x_i - \bar{x}}{\sigma^x}\right)\left(\frac{y_i - \bar{y}}{\sigma_y}\right) \tag{7}$$

where n is the number of records in the original data table, x_i, y_i is the current record value of different data columns, σ^x, σ_y is the standard variance, and x, y is the mean. In the formula, you need to calculate the number of records in the original table, as well as the mean and standard deviation of each numerical column.

In this paper, the matrix-based Apriori algorithm is optimized and improved by combining the idea of parallelization with the idea of itemset sorting. Try to divide the transaction database into data blocks with the same size and no intersection with each other, and then start multiple threads to scan the segmented data blocks respectively. The transaction sets are initialized as Boolean matrices. With the increase of iteration times, the generation of infrequent candidate sets is more and more reduced than that without sorting. However, the time consumed by quick sorting is relatively short, and the advantages of sorting are more and more obvious, so sorting can reduce the iteration time.

ID3 algorithm tends to choose attributes with more attribute values as attribute selection metrics when using information gain to select attributes. The formula for calculating the information gain rate is as follows:

$$GainRatio(A) = \frac{Gain(A)}{SplitInfo(A)} \tag{8}$$

When a bit is 1, the attribute exists; otherwise, it does not exist. Each bit string is a candidate for reduction. Define the fitness function as follows:

$$F(v) = \frac{N - L_v}{N} + \frac{C_v}{(m^2 - m)/2} \tag{9}$$

where N is the length of the attribute set and L_v is the number of 1 in v. C_v is the number of object combinations that v can distinguish. m is the number of objects.

The process of Apriori algorithm can be clearly presented in **Figure 2** below:

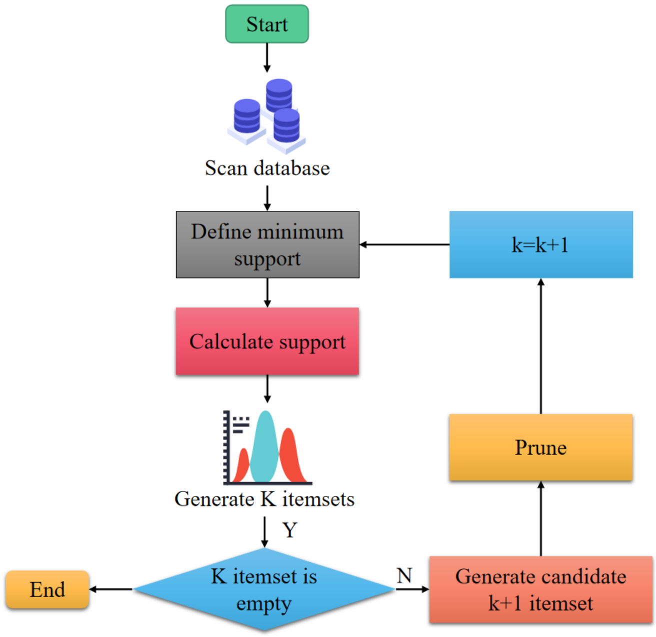

Figure 2. Apriori algorithm flow chart.

The application of Apriori algorithm is roughly divided into the following steps:

1) Scanning the database, and counting the support degree of each $k = 1$ item set;
2) According to the frequent 1 item set generated in step 1, a new candidate 2 item set is generated.
3) By scanning the whole database, the support degree of each candidate set in the candidate k itemsets is calculated, and the candidate itemsets whose support degree is less than the minimum support degree are deleted, leaving the frequent k-itemsets that meet the conditions;
4) Iterate until the k step, when a new frequent itemset cannot be generated.

3. Result analysis

Appropriate exercise goals can meet the needs of individual abilities, produce individual efforts and exercise persistence, and point out directional behaviors. Appropriate goals can also form certain behavior strategies, and in the process of achieving the goals, they can generate interest and motivation to participate in exercise. Therefore, the setting of exercise goals plays an important role in the generation of exercise motivation.

In order to explore the specific effects of different intensity of exercise and different goal settings on college students' PE habits, this study compares the indexes of the pre-and post-test of each experimental group. The specific results show that there are significant differences in the intensity of PE habits of subjects with moderate exercise intensity and different goal settings before and after the intervention, but in the pre-, post-and follow-up tests of PE habits. The results are shown in **Figure 3**.

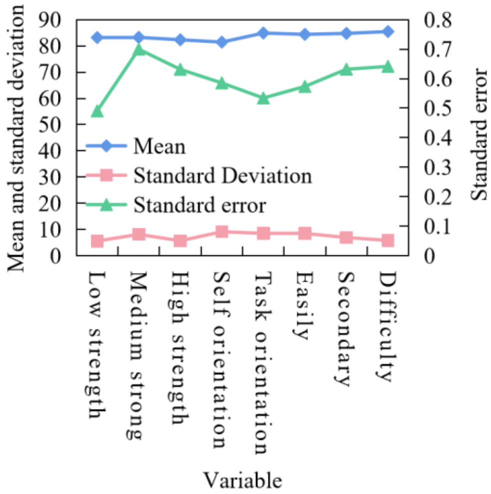

Figure 3. Statistical description between different levels of variables.

It can be seen that after the intervention, the influence of moderate intensity exercise, task orientation and moderate difficulty goal on the PE habit intensity is much higher than that of low intensity and high intensity students, and there are significant differences among the factors. There is no significant difference in the influence of high and low intensity on exercise habits, and there is no significant difference in the influence of easy goals and difficult goals on the formation of exercise habits. Under the task orientation, the intensity of PE habits of all college students with different target difficulty has increased to varying degrees.

In order to explore the specific influence of different exercise intensity and different goal setting on college students' exercise motivation, this study compares the indexes of each experimental group before and after the test, and the specific results are shown in **Table 1**.

Table 1. Test of intersubjective effect.

	df	**Mean square**	***F***	**Sig.**
Correction model	1	4002.151	694.682	0.000
Intercept	13	3782.156	691.912	0.000
Pre-test exercise motivation	10	3719.024	683.161	0.000
Intensity	9	3833.922	725.327	0.000
Target orientation	13	3611.604	690.869	0.000
Target difficulty	3	4414.971	684.988	0.000

Pre-test scores have influence on post-test scores. Under the condition of controlling the covariates, exercise intensity has main effect, which indicates that different exercise intensities have significant differences on exercise motivation. The interaction among exercise intensity, goal orientation and goal difficulty is also statistically significant, which indicates that different exercise intensities and goal settings have different effects on college students' exercise motivation.

PE helps to establish good interpersonal relationships. Fourth, PE can produce a sense of fulfillment and satisfaction. A variety of extracurricular sports activities can make college students increase their knowledge, develop their talents and produce a sense of fulfillment. Participants often get pleasure and joy, favor and satisfaction from it, etc., which can eliminate tension, hone people's character, exercise people's will and improve people's MH. The influence of PE on college students' MH is reflected in different psychological factors. See **Table 2**.

Table 2. Comparison of the influence of PE on college students' MH development.

Psychological factors	Exercise regularly	Don't exercise regularly	*t*
Somatization	1.942 ± 0.41	1.707 ± 0.21**	4.042*
Force	1.747 ± 0.53**	1.769 ± 0.36**	2.747*
Interpersonal relationship	1.611 ± 0.66**	2.034 ± 0.71**	3.899*
Depressed	1.844 ± 0.14**	1.989 ± 0.52**	2.838*
Anxious	1.626 ± 0.52	1.694 ± 0.29**	3.937*
Hostile	1.584 ± 0.35**	1.858 ± 0.17**	3.485*
Terrifying	1.668 ± 0.28	2.068 ± 0.66**	3.929
Sstubbornly biased	1.729 ± 0.71**	2.117 ± 0.58**	3.389*
Psychosis	1.882 ± 0.61	1.74 ± 0.23**	2.663*
Positive items	41.698 ± 15.29**	47.024 ± 13.18**	3.004*

Note: "* *" means $P < 0.01$ compared with the norm of normal peers, *t* value means that regular exercisers are compared with infrequent exercisers, and "*" means $P < 0.05$.

It is found that the symptoms of 9 factors of regular exercisers are obviously lower than those of infrequent exercisers, which indicates that the MH level of college students who regularly take part in PE is higher than that of infrequent exercisers. *T*-test ($P < 0.05$) shows that, except somatization and terror, there are significant differences in other seven psychological factors of college students who often take part in PE compared with those who don't.

Through abnormal DM, we can know the scores of each college student in various aspects, that is, the projection values of each data object in ten factors, and the comprehensive MH. So far, ten factors can be set as class labels, and the corresponding rules can be mined. We adopt the method of data expansion, that is, the data objects that are "serious" or "obvious" are multiplied. The choice of parameters is often related to the corresponding data set. We choose two parameters through experiments. See **Figure 4** for the results.

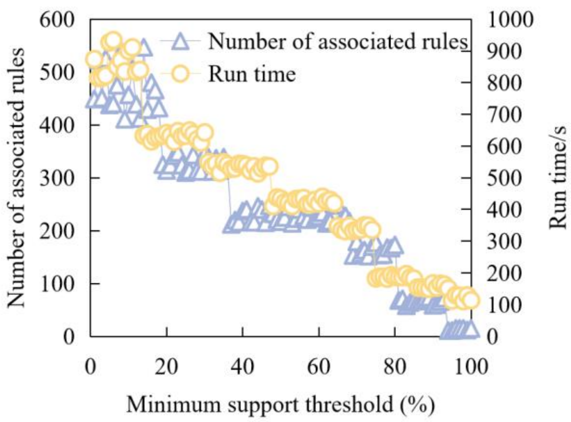

Figure 4. Mining association rules.

Education, with its unique activity form, rich content, and combination of physical and intellectual challenges, ensures that physical education (PE) and health promotion are closely interconnected and mutually reinforcing. Specialized training in a variety of sports allows students to develop specific athletic skills, which in turn leads to positive emotional experiences during exercise and boosts their enthusiasm for participation. These experiences lay a solid foundation for achieving a high health quotient and improving overall quality of life. PE not only helps college students establish social support networks but also teaches them how to provide meaningful support to society.

As data sets are continuously decomposed, each subset becomes smaller, which can lead to issues such as fragmentation, duplication, and redundancy in the constructed decision tree (DT). Fragmentation occurs when the number of samples in a particular branch becomes too small, rendering the results statistically insignificant.

Typically, data sets are vast, and the scalability of existing DT algorithms is severely limited due to inherent constraints. The primary challenge is that, during the construction of DTs, continuous data exchange between internal memory and external storage results in poor data mining (DM) performance. Additionally, the classification accuracy of DTs may fall short compared to that of a single classifier trained on the entire data set. The performance of these algorithms is typically evaluated based on time, and experimental results for different algorithms are illustrated in **Figures 5–7**.

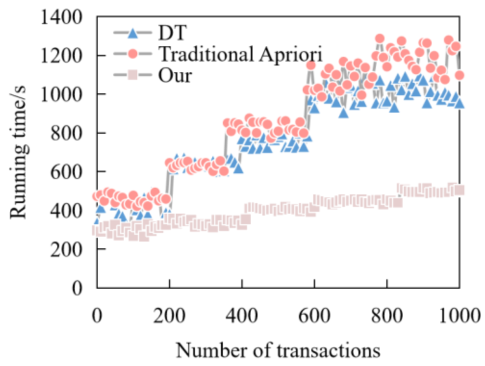

Figure 5. Comparison of running time of algorithms in different transaction databases.

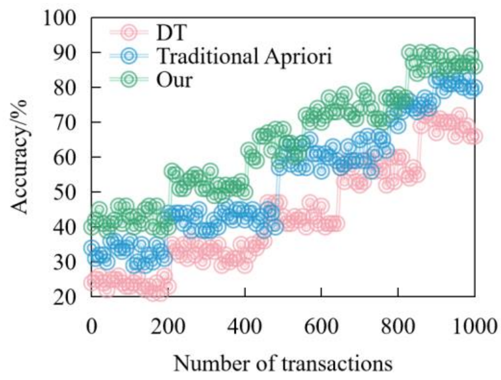

Figure 6. Comparison of running accuracy of algorithms in different transaction databases.

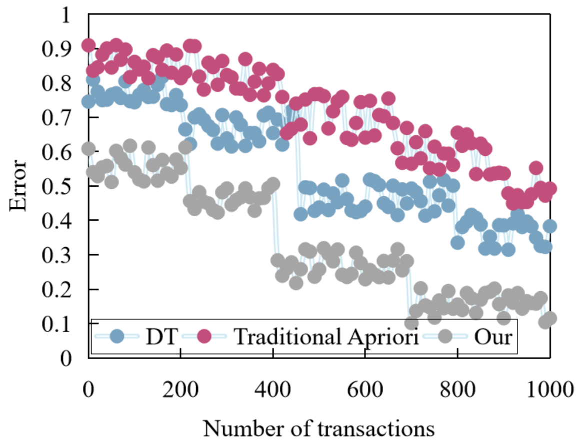

Figure 7. Comparison of running errors of algorithms in different transaction databases.

We can clearly see that the running time of the other two matrix-based improved Apriori algorithms is greatly reduced compared with the original Apriori algorithm, and the running time of the original Apriori algorithm increases linearly with the number of transactions. In the process of iteration, the generation of many infrequent item candidate sets is reduced. As the number of transactions increases, the advantages of parallel operation and sorting will become more and more obvious. Compared with the comparison algorithm, the accuracy of the improved algorithm is increased by 23.68%, and the running time is reduced by 10.17%.

In physical education classroom teaching, first of all, we should change students' one-sided understanding of physical education, make them understand the importance of physical education, attach importance to physical education class and actively participate in physical education classroom; Secondly, teachers use scientific teaching methods to enable students to master motor skills and improve their physical quality. Replace the venting of negative emotions through strenuous exercise. This can provide an outlet for all kinds of stagnant negative emotions, transfer the impulse generated after suffering setbacks through sports activities, and weaken or eliminate emotional barriers.

4. Discussion: Biomechanics, physical activity, and mental health

The findings of this study underscore the significant role of biomechanics in linking physical exercise to mental health improvements, particularly among college students. Biomechanical mechanisms, such as neuromechanical feedback, play a crucial role in enhancing mental well-being. Activities like running or swimming stimulate mechanoreceptors and proprioceptors, triggering neurochemical changes, including the release of endorphins and serotonin, which are known to reduce stress and anxiety. Moreover, increased cerebral blood flow during physical activity supports brain function and emotional regulation, highlighting the physiological underpinnings of the mental health benefits associated with exercise.

This research also demonstrates the value of data mining in understanding the relationship between exercise and mental health. The application of an optimized Apriori algorithm not only identifies significant associations between exercise habits and psychological factors but also facilitates the development of tailored interventions. For instance, exercise programs can be customized to address specific mental health challenges, such as anxiety or depression, by focusing on activities that maximize biomechanical and neurochemical benefits. These insights emphasize the importance of using data-driven approaches to enhance physical education and mental health outcomes.

Finally, the practical implications for physical education programs are evident. Universities should incorporate biomechanics-based strategies into their curricula, providing students with the knowledge and opportunities to engage in targeted physical activities. This includes designing interventions that encourage participation through improved facilities and tailored programs. Such efforts can foster a supportive environment where students not only develop their physical fitness but also enhance their mental resilience, social skills, and overall well-being.

5. Conclusion

Physical education (PE) and mental health (MH) are becoming increasingly intertwined, with students who regularly engage in PE experiencing significantly lower levels of psychological pressure compared to those who do not. However, not all forms of PE are equally effective. Proper choices should be made based on the principles of physical and mental development, as well as individual differences among college students. Education, with its unique activity form, rich content, and combination of physical and intellectual challenges, ensures that PE and health promotion are closely interconnected and mutually reinforcing.

In this study, the matrix-based Apriori algorithm is optimized and improved by integrating parallelization with itemset sorting. The transaction database is divided into equally sized, non-overlapping data blocks, and multiple threads are employed to scan these blocks simultaneously. As the number of transactions grows, the benefits of parallel processing and sorting become increasingly apparent. Compared to the baseline algorithm, the improved version demonstrates a 23.68% increase in accuracy and a 10.17% reduction in runtime.

Ethical approval: Not applicable.

Informed consent: Not applicable.

Conflict of interest: The authors declare no conflict of interest.

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