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Retraction

Retracted: Value Assessment for a Theory-Oriented Flipped Classroom of Physical Education Based on Multi-Source Data Analysis

Security and Communication Networks

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope
(2) Discrepancies in the description of the research reported
(3) Discrepancies between the availability of data and the research described
(4) Inappropriate citations
(5) Incoherent, meaningless and/or irrelevant content included in the article
(6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] N. Li, "Value Assessment for a Theory-Oriented Flipped Classroom of Physical Education Based on Multi-Source Data Analysis," *Security and Communication Networks*, vol. 2022, Article ID 6540710, 9 pages, 2022.

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Research Article

Value Assessment for a Theory-Oriented Flipped Classroom of Physical Education Based on Multi-Source Data Analysis

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In order to overcome the problem of students' boredom in physical education theory classes in general, and to give full play to the role of assessment in guiding, diagnosing, motivating and proving, this paper analyses the multi-source data generated during the teaching process, which can predict students' subsequent learning status. Based on the collection and processing of data from multiple sources, this study takes the PE course as an example and predicts the course performance based on multiple dimensions; and carries out empirical analysis with the actual course performance through numerical correlation, ranking correlation and the bottom band. The analysis was compared with actual course grades through numerical correlation, ranking correlation and bottom band warning coverage of students. The results of the study show that the earliest grade prediction using taught courses has the highest student warning coverage; the highest grade prediction based on unit tests has the highest numerical relevance and ranking relevance; and the highest grade prediction based on unit tests has the highest student warning coverage.

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1. Introduction

Since the 21st century, with the continuous progress and development of information technology in education, how to integrate computer-related technology with the field of physical education has gradually formed an important research direction [1]. Smart education based on modern information technology has received great attention at the national level. In the field of professional sports theory courses, the rapid development of the Internet and various digital terminals has promoted big data research, and data analysis has shown great potential in improving the quality of education, optimising the learning process and improving the learning experience [2, 3]. Educational data analytics is used as a supporting technology for building smart education, for understanding and optimising the learning process and learning context [4]. Learning analytics is used to monitor and evaluate the learning process [5–7]. Al Aufi and Rao Naidu [8] constructed a personalized adaptive online learning analysis model based on online teaching data, which can be applied to personalized resource delivery and learning result analysis. The use of process evaluation based on big data can effectively promote adaptive development of learners. Cross-domain correlation and data analysis based on educational big data from multiple data sources can uncover hidden phenomena and patterns in the teaching and learning process, which is conducive to assisting decision-making in physical education [9].

According to the students interviewed, the process performance assessment enables students to understand their learning situation in a timely manner and guide their learning behaviour correctly, especially that a test paper is no longer used to assess the degree of knowledge mastery [10–12]. In particular, instead of using a test paper to assess knowledge mastery, students' attitudes, values, behaviours and abilities are included in the assessment, and a "point system" is used to record students' learning behaviour, which effectively guides their learning behaviour. Students' satisfaction with the indicators of "classroom participation, classroom order, classroom communication and cooperation" is high, with an average score of 4.5 or above. The classroom atmosphere is particularly good, as every student has the opportunity to participate in the classroom. Students' satisfaction with the indicators of "knowledge acquired, emotions developed and skills learnt" is high, with an average score of over 4.6. Information technology application skills have been improved to different degrees [13].

Big data in education records data on students' basic information, campus life, classroom learning and extracurricular learning, which can be used to assess current academic status as well as to predict students' future performance and academic early warning [14–17]. The research and application of big data in education is entering a phase of rapid development, but there are still the following problems: (1) the extent of data in education is further strengthened, and the variety and total amount of data is increasing, but the education and teaching mode has not changed substantially as a result, and smart education based on big data in education still has a long way to go. This paper aims to collect and analyse data from multiple sources in the teaching and learning process to investigate the learning status and effectiveness of students and to predict the learning status of students in the course. The course is based on the collection and processing of data from multiple sources.

1.1. Data Collection. Make full use of modern information technology to further optimise the structure of classroom teaching, so that students can learn and communicate in class, reducing the time for teachers to teach in class and increasing the time for tutorials and question and answer sessions in class, further optimising the structure of classroom teaching and improving the efficiency and quality of teaching [18]. This will reduce the time spent on lectures and increase the time spent on question and answer sessions, further optimising the classroom teaching structure and improving the efficiency and quality of classroom teaching [19].

Improve the classroom learning behaviour contract to guide students' independent learning and self-management [19]. The classroom teaching management system should not be a cold rule, but a classroom learning behaviour contract agreed upon by teachers and students, with clear boundaries of classroom behaviour standards for better fulfilment of the contract [20].

Adding evaluation criteria for cooperative group learning and strengthening guidance and monitoring of the learning process in learning groups [21]. In order to promote cooperative learning in learning groups and to supervise communication, discussion, collaboration and reflection among peers, improvement measures are as follows: (a) guide learning groups to draw up a common learning contract and evaluation criteria, and to conduct self-assessment and mutual assessment of group members; (b) explain and explain group assignments and ways and means of completing them; (c) guide (c) guiding learning groups to make full use of each other's strengths and resources to complement each other's weaknesses; (d) adding evaluation criteria for group work sharing and collaboration to encourage mutual monitoring among learning groups.

The same correlation analysis was conducted for the 2013 year group. The correlation values between Physical Education courses and other core course for the 2013 and 2014 years were extracted and constructed into Table 1, and the values were averaged for both years [22]. From Table 2 can be seen that the three courses with the highest correlations are Computer Networking, Physical Education and Object-Oriented Programming, indicating that they have the greatest influence on each other. However, the Physical Education course was offered before Physical Education and Computer Networking, and these courses with later chronology cannot be used as a basis for prediction. Therefore, Table 1 selects the three pre-trending courses that are ahead of the chronological order as the basis for prediction, and the values of their correlation coefficients are averaged and then normalised to form the corresponding weighting coefficients.

The way in which a course grade is predicted from an existing core course grade is shown in equation (1):

$$ForrScore = \sum_{i=1}^{m} \left(q_i' \times \text{Score}_{\,i}\right). \tag{1}$$

In equation (1), the Forr Score represents the individual grade for the predicted course and is calculated by multiplying the weighting factor q_i' with the previous trend course grade and summing.

The predicted grades for the PE course are obtained by equation (1) and ranked within the group. The students who are lagging behind in their predicted performance (e.g. the last 15% of students, 12 students, whose numbers and names have been treated accordingly to protect their rights) can be identified [23].

This group of students can be educated in advance by communicating with the class teacher and the lecturer, and by providing focused attention and intervention during the teaching process to strengthen the process of control.

1.2. Reversing the Classroom Model Set-Up. The Technology Acceptance Model (TAM) was proposed by Davis in 1989, as shown in Figure 1, and includes perceived usefulness, perceived ease of use, attitude towards use and behavioural intention [24]. Numerous empirical studies have found that TAM mostly explains differences in usage intentions and behaviour. Perceived usefulness and perceived ease of use are the main measures of technology acceptance behaviour, with perceived usefulness being the user's perceived ability to bring performance to the job, perceived ease of use being the user's perceived ease of use of the technology, and attitude towards use being the mediating variable between perceived usefulness and perceived ease of use, which acts to influence behavioural intentions and thus the actual behaviour of the user [25]. TAM indicates that the user's The higher the perceived ease of use and perceived usefulness, the more positive their attitudes towards use will be, and the stronger the influence of perceived usefulness and perceived ease of use in the early stages of learning and behaviour [26]. The flipped classroom uses a platform for online learning and discussion, therefore, TAM was chosen as the theoretical support to determine students' acceptance of the flipped classroom.

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Table 1: Correlation statistics between physical education courses and core courses of the major for both cohorts.

	Operating system (level 14)	Operating system (level 13)	Average value	Forward normalization
C language programming	0.18	−0.06	0.06	0.09
Data structure	0.17	0.39	0.28	0.41
Object oriented programming	0.21	0.48	0.34	—
Operating system	0.22	0.34	0.28	—
Database principle	0.19	0.41	0.3	—
Algorithm design and analysis	0.5	0.2	0.35	—
Computer network	0.45	0.27	0.36	—

Table 2: Correlation analysis between the core courses of the major for the class of 2014.

Correlation coefficient	C language programming	Data structure	Object oriented programming	Operating system	Database principle	Algorithm design and analysis	Software engineering	Computer network
C language programming	1	0.33	0.26	0.18	0.12	0.16	0.18	0.33
Data structure	0.33	1	0.22	0.17	0.1	0.02	0.1	0.2
Object oriented programming	0.26	0.22	1	0.21	−0.03	0.31	0.42	0.45
Operating system	0.18	0.17	0.21	1	0.22	0.19	0.5	0.45
Database principle	0.12	0.1	−0.03	0.22	1	0.14	0.28	0.15
Algorithm design and analysis	0.16	0.02	0.31	0.19	0.14	1	0.48	0.37
Software engineering	0.18	0.1	0.42	0.5	0.28	0.48	1	0.6
Computer network	0.33	0.2	0.45	0.45	0.15	0.37	0.6	1

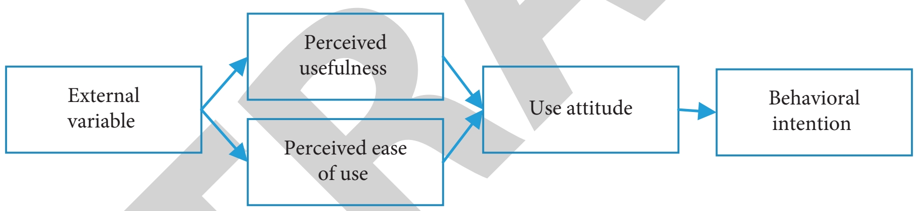

Figure 1: Technology acceptance model (TAM).

This study is based on TAM and guided by the Expected Value Theory and Collective Efficacy Theory to design a model of student problem solving skills in accordance with the flipped classroom model, as showed in Figure 2.

The structural model consists of three components: TAM, task factors and collective efficacy.

Firstly, the TAM component consists of the potential variables of ease of use of the platform, usefulness of the flipped classroom model, and acceptance of the flipped classroom model. The TAM component is designed to observe the usefulness and ease of use of the platform and online course. The ease of use of the platform and online course will reduce the disruption of the learning process and ensure that learners learn smoothly. The ease of use of the platform and the usefulness of the flipped classroom model in turn have an impact on the acceptance of the flipped classroom model, so that the increased ease of use of the platform and the usefulness of the flipped classroom model will lead to learner acceptance of the flipped classroom model and thus motivate students to learn. Therefore, hypotheses H1, H2 and H3 are proposed in this study [27].

The next component was the task factor. According to the Expected Value Theory, when students perceive the value of a task assigned by the teacher to be high, they will try to complete the task to maximize the value of the task, i.e. their motivation will increase accordingly. Therefore, hypothesis H4 is proposed.

Finally, the collective efficacy component consists of three potential variables: individual evaluation, group evaluation and problem-solving ability. According to the theory of collective efficacy, in independent learning, students who are sure of their own abilities and complete the corresponding learning tasks will be motivated by the evaluation of task completion, and in group learning, students who evaluate their own group and believe in their peers will be motivated accordingly. The increase in motivation can lead students to solve difficulties in the learning process and thus improve their problem solving skills. Therefore, hypotheses H5, H6 and H7 are proposed in this study.

2. Empirical Research Process and Results

The course "Database" was chosen as the experimental course, with three consecutive classes per week, and the experimental period was 18 weeks in total. First, the course

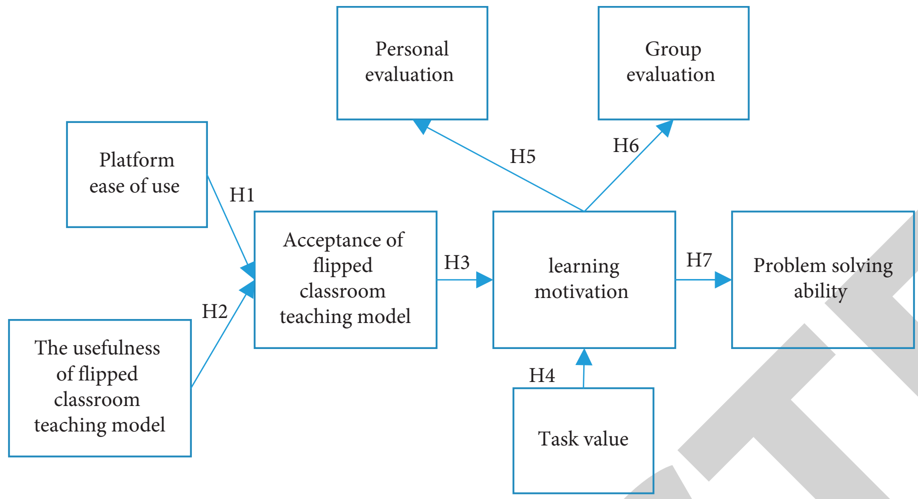

Figure 2: Student problem solving skills model.

instructor recorded online videos (15–20 minutes/video) and collected resources related to the course, and the teacher observes the number of times learners watch the videos and the progress of the videos through the TronClass backend to keep track of learners' learning progress. In addition, when learners encounter doubts during online learning, they can ask and answer questions in the course discussion module, through which teachers can grasp the difficulties in the learning process and the learning status of learners [28]. The teacher focuses on difficult questions to broaden students' horizons, deepen their knowledge construction and develop their creative thinking. Relevant data by the pedagogues, to grasp the teaching progress and to improve the quality of the lessons [29].

Figure 3 represents the distribution of the predicted grades based on the professional course and the actual course grades, with the horizontal coordinates being the individual student serial numbers and the vertical coordinates being the grade values. The correlation between the two sets of data is 0.67, indicating a good correlation between predicted and actual grades (The y-axis represents the score, and the x-axis represents the video length)

The two sets of data were ranked within groups separately and displayed as showed in Figure 4. The correlation of the rankings was 0.73, which was higher and higher than the correlation of the numerical values. This indicates that students' rankings have a higher degree of stability and that individuals' within-group learning ability and attitude towards learning are more stable across different specialised courses, significantly higher than the correlation with the numerical value of grades that are more strongly correlated with the specific content studied. (The y-axis represents the score, and the x-axis represents the ranking)

Figure 4 lists the last 12 actual grades in the PE course (representing 15% of the students in both classes) and shows that nine of the last 12 students predicted appeared in the last 12 of the actual grades, giving a prediction accuracy of 75%.

The unit tests indicate students' attitudes and stage learning outcomes, and these data can clearly be applied to course early warning with the advantage of real-time, dynamic updates (as the number of unit tests increases, the stability and accuracy of the predicted results will increase).

The numbers on the horizontal coordinates in Figure 5 represent the first N unit tests, and the average of the first N unit test score is used to represent the predicted course grade; the numbers on the vertical coordinates represent the correlation coefficient. The correlation coefficient between the average of the first two unit tests and the actual grade of the course is 0.56. From the change in height of the bars, the correlation coefficient between the average of the unit tests and the actual grade of the course gradually increases and stabilises as the number of unit tests increases, and the correlation coefficient between the average of six unit tests and the actual grade of the course is as high as 0.79, reflecting a high correlation. This shows a high correlation [12].

The correlation coefficient between the mean of the six unit tests and the actual course grade was 0.79, showing a high correlation. This indicates that it is feasible to predict the course by the mean of the course unit test score. In addition, the method is dynamic and progressive: the initial prediction can be made after the first unit test of the course, and the correlation with the final grade of the course is low due to the small number of statistics; however, as the number of lectures and unit tests increases, the statistics cover more of the course and show the academic performance of individual students at more stages in time. So the correlation continues to increase and stabilise as showing in Figure 6. (The y-axis represents the grade, and the x-axis represents the course)

With the increasing popularity and use of smart teaching tools and online teaching platforms, an increasing amount of data is being generated on the mobile and PC side of the Internet. In this paper, the data from the mobile teaching data (Rain Classroom data) and the data from the virtual simulation experimentation platform (Experiment Building data) are collected and counted separately to develop course performance predictions. The combination of the two is further investigated and analysed.

The classroom data are mainly derived from the multiple-choice questions and attendance in the theory class of the PE course, which can reflect the students' participation,

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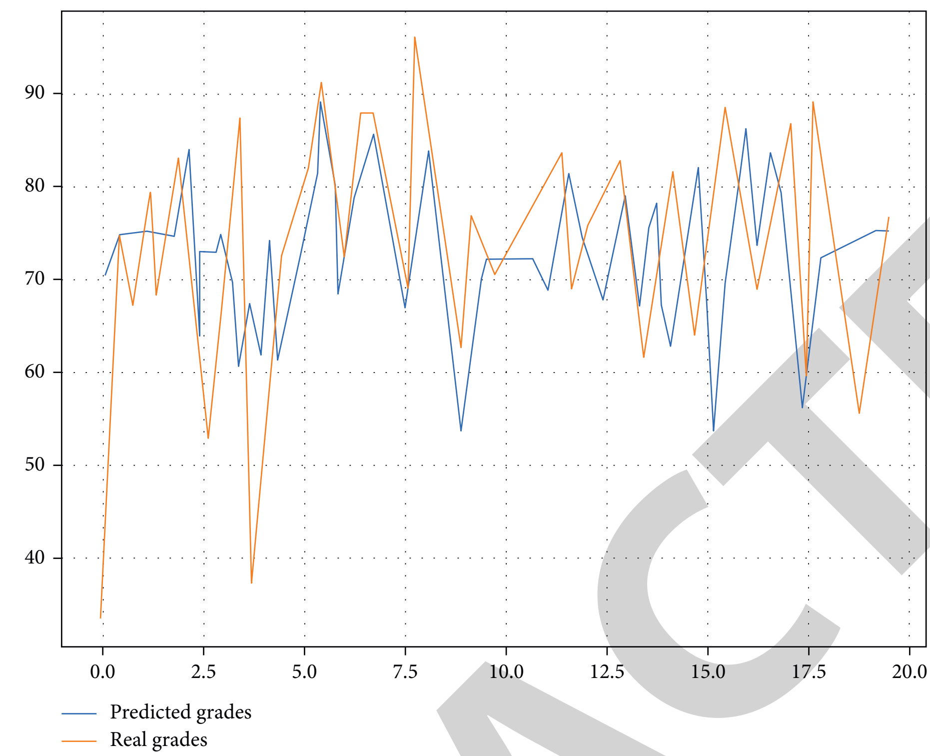

Figure 3: Diagram showing predicted and actual grades based on relevance to the major.

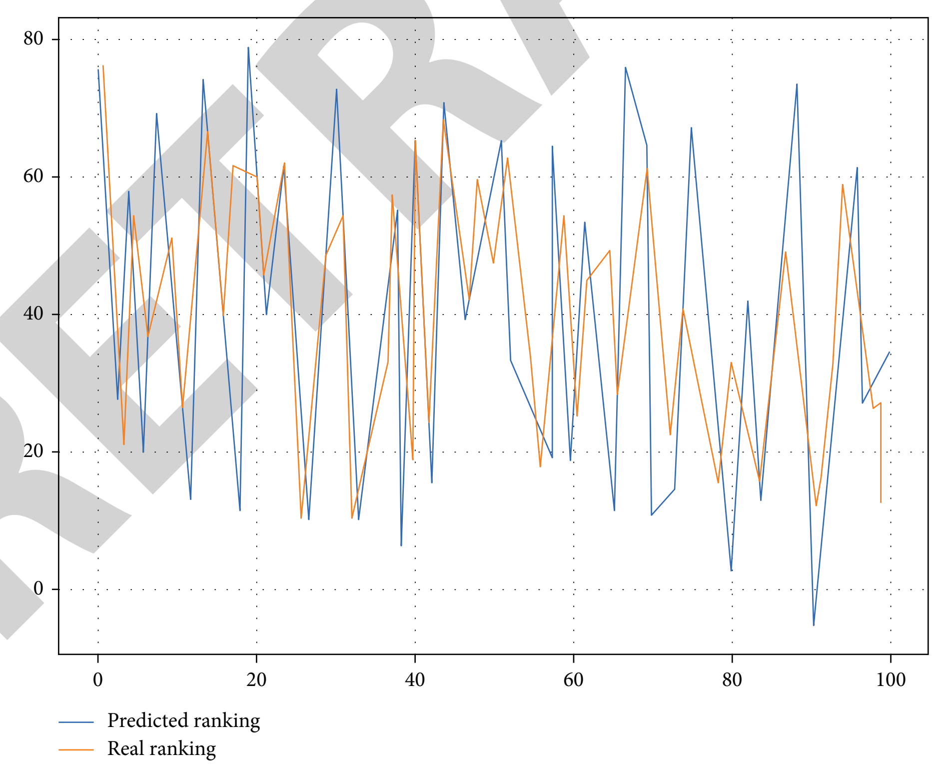

Figure 4: Diagram showing predicted and actual ranking based on relevance of major courses.

concentration and learning effect in the theory class. But the data is also fragmented and not systematic.

These data were standardised according to a percentage system, so that the values for each individual student were converted to a numerical space from 0 to 100, and this value was used to represent the predicted grades based on the rain classroom data [30]. The predicted and actual grades based on the Rainy Classroom data are shown in Figure 7, with a

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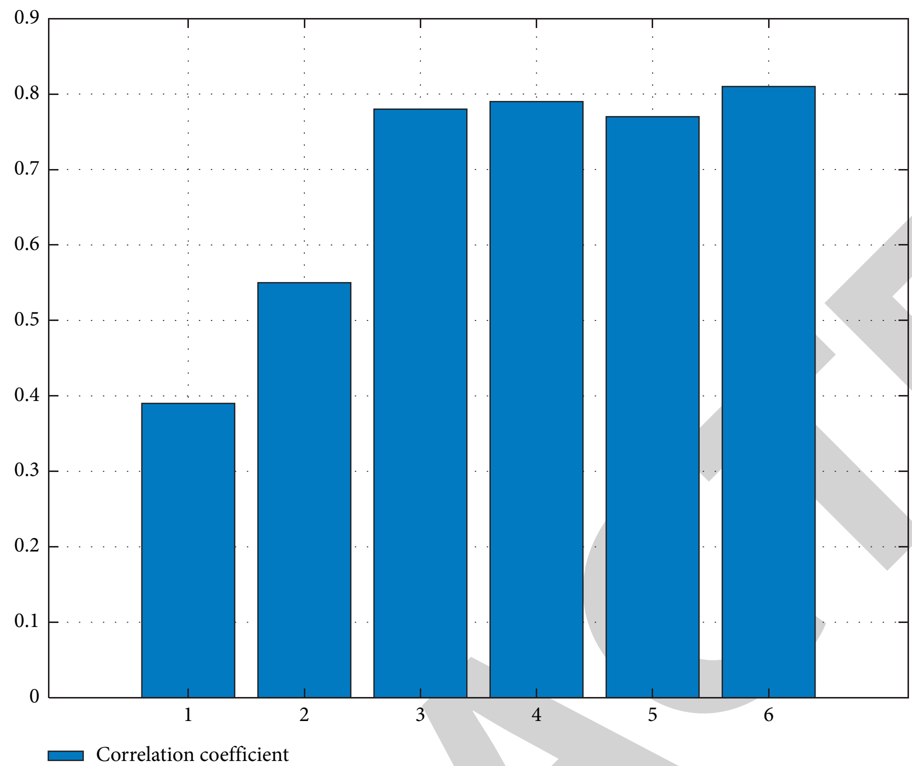

Figure 5: Correlation between predicted and actual scores based on the first N unit tests.

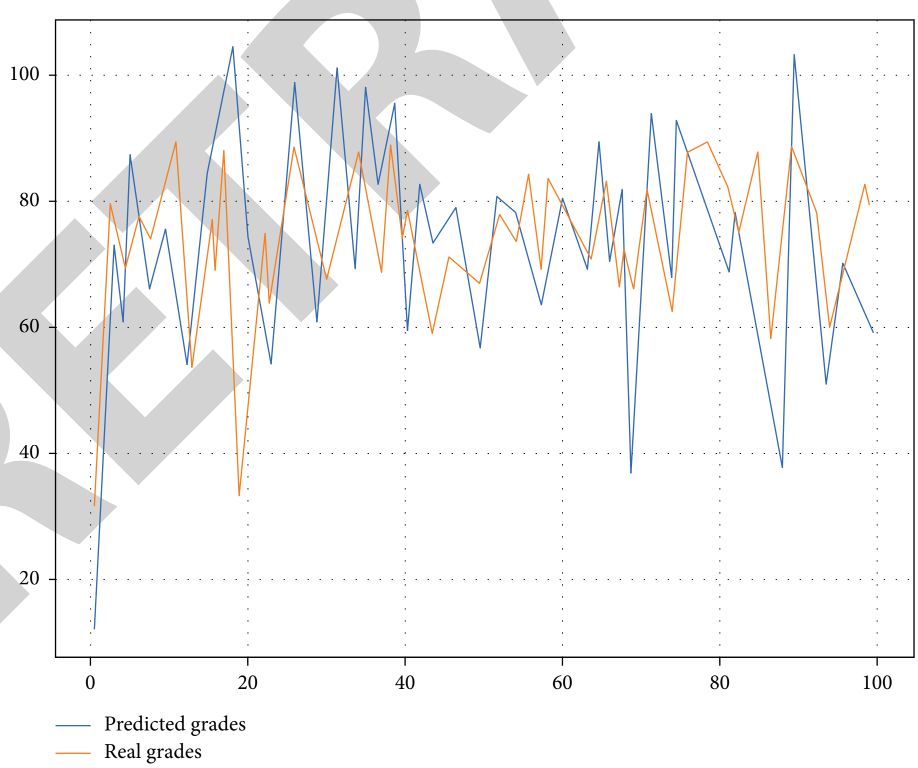

Figure 6: Schematic representation of predicted and actual grades based on unit tests.

correlation coefficient of 0.67; the two sets of data were then ranked within the group, with a correlation coefficient of 0.60. Finally, the bottom 15% of the group was compared with the bottom 15% of the actual grade based on their ranking, and six students were predicted, with a prediction accuracy of 50% for the early warning students. (The y-axis represents the grade, and the x-axis represents the course).

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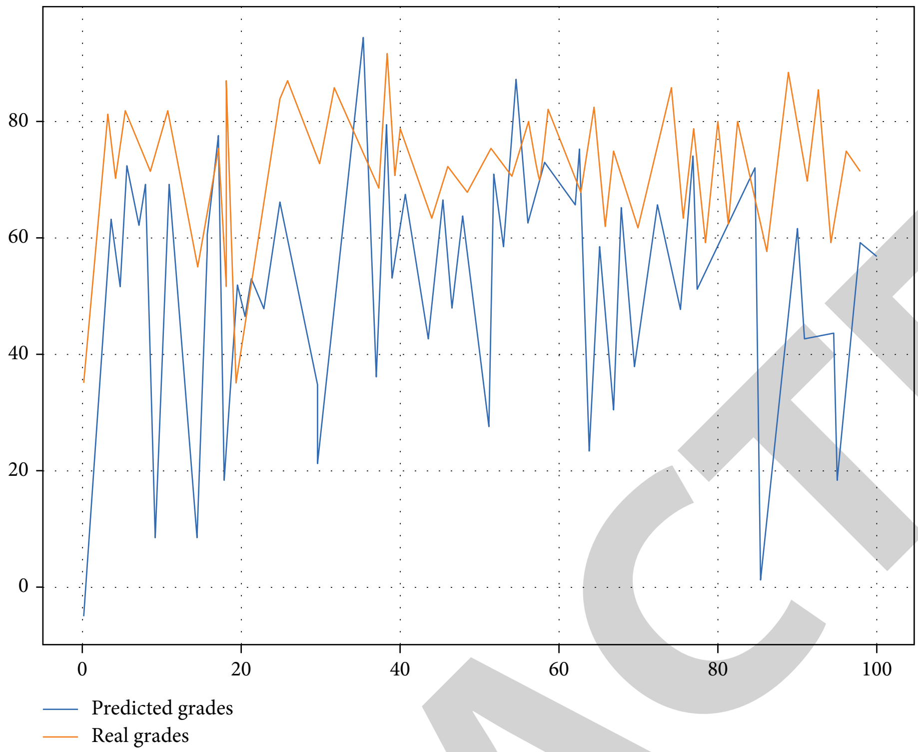

FIGURE 7: Diagram showing predicted and actual grades based on rain classroom data.

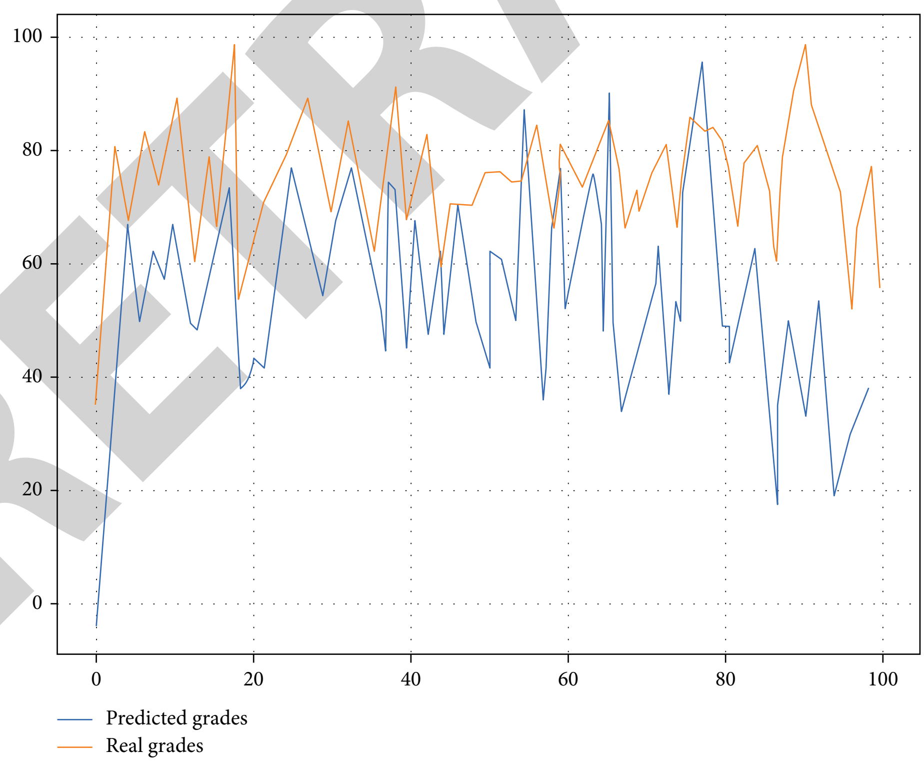

FIGURE 8: Schematic representation of predicted and actual grades based on experimental building data.

Experimental building data in this paper use only the indicator of total effective learning time, which represents the total effective learning time that students put in during the experimental sessions of the physical education course. These data were normalised according to a percentage scale, allowing each individual student's value to be converted to a numerical space from 0 to 100, and this value was used to represent the predicted grades based on the laboratory

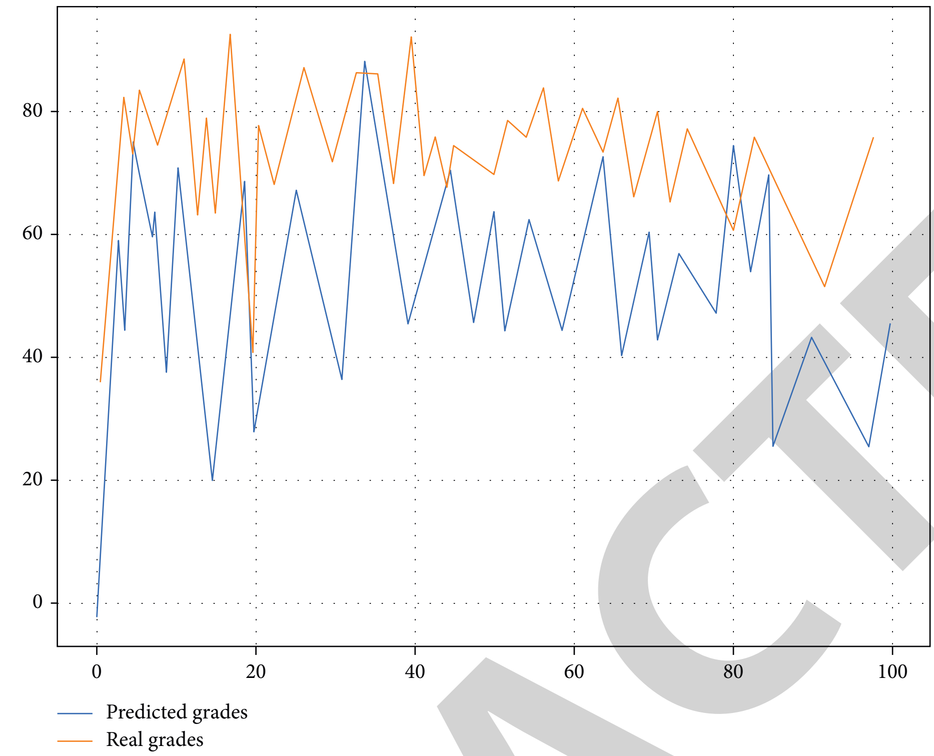

FIGURE 9: Diagram showing predicted and actual grades based on the combined online teaching data.

building data. Further, a correlation analysis was performed with the actual grades of the students to obtain Figure 8. (The y-axis represents the grade, and the x-axis represents the course).

The correlation coefficient between the predicted and actual grades based on the experimental building data was 0.60; subsequently, the correlation coefficient between the ranking of the two groups was 0.57, which is about the same as the numerical correlation. Finally, the students in the bottom 15% of the group were extracted based on their ranking and compared to the bottom 15% of the actual grade, and five students were predicted, giving an accuracy rate of 41.7% for early warning students.

As both the rain classroom data and the lab floor data were derived from students' daily classroom performance, the former from theory classes and the latter from practical classes, the two sets of data were normalised (converted to a 0–100 value space) and then averaged to obtain a set of predicted scores. As these data are sourced from the online teaching platform, they are referred to as predicted grades based on online teaching data. The exact distribution of the predicted and actual scores is shown in Figure 9. (The y-axis represents the grade, and the x-axis represents the course).

The correlation coefficient between the predicted and actual grades based on online teaching data was 0.72. Subsequently, the correlation coefficient between the two sets of data was 0.70 when ranked within the group, which is a significant increase in correlation compared to the prediction based on the rain classroom data only and the prediction based on the laboratory building data only, indicating a more accurate prediction.

3. Conclusions

In this paper, based on the collection and processing of data from multiple sources of teaching, course performance prediction is carried out based on a total of five dimensions: taught professional courses in physical education theory courses, unit tests, mobile teaching data, virtual simulation experiment data and comprehensive data from online teaching; and correlated with actual course performance by numerical correlation, ranking correlation and warning coverage of students in the bottom segment. The method with the highest numerical correlation and the method with the highest ranking correlation was Method 2. This indicates that there is a high correlation between unit tests and course tests in terms of knowledge and test content, and that course grade prediction based on unit test data is more accurate.

Data Availability

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Conflicts of Interest

The authors declared that they have no conflicts of interest regarding this work.

Acknowledgments

No funding was used in this study.

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References

[1] C. Stöhr and T. Adawi, "Flipped classroom research: from "black box" to "white box" evaluation," *Education Sciences*, vol. 8, no. 1, p. 22, 2018.

[2] H. Li, D. Zeng, L. Chen, Q. Chen, M. Wang, and C. Zhang, "Immune Multipath Reliable Transmission with Fault Tolerance in Wireless Sensor Networks," in *Proceedings of the International Conference on Bio-Inspired Computing: Theories and Applications*, pp. 513–517, China, October 2016.

[3] B. Huang, K. F. Hew, and C. K. Lo, "Investigating the effects of gamification-enhanced flipped learning on undergraduate students' behavioral and cognitive engagement," *Interactive Learning Environments*, vol. 27, no. 8, pp. 1106–1126, 2019.

[4] C. H. Cao, Y. N. Tang, D. Y. Huang, G. WeiMin, and Z. Chunjiong, "IIBE: An Improved Identity-Based Encryption Algorithm for Wsn Security," *Security and Communication Networks*, vol. 2021, Article ID 8527068, 2021.

[5] M. Lundin, A. Bergviken Rensfeldt, T. Hillman, A. Lantz-Andersson, and L. Peterson, "Higher education dominance and siloed knowledge: a systematic review of flipped classroom research," *International Journal of Educational Technology in Higher Education*, vol. 15, no. 1, pp. 20–30, 2018.

[6] C. Stöhr, C. Demazière, and T. Adawi, "The polarizing effect of the online flipped classroom," *Computers & Education*, vol. 147, p. 103789, 2020.

[7] E. Colomo-Magaña, R. Soto-Varela, J. Ruiz-Palmero, and M. Gómez-García, "University students' perception of the usefulness of the flipped classroom methodology," *Education Sciences*, vol. 10, no. 10, p. 275, 2020.

[8] A. Al Aufi and V. Rao Naidu, "Students' perception of the use of learning management system to facilitate flipped learning experience for English language teaching in private higher education institution in Oman: a developmental evaluation," *Arab World English Journal*, vol. 2, pp. 360–377, 2020.

[9] C. Stöhr and K. Färnevik, "May online blended learning in corporate training enhance lifelong learning? Experiences from Artificial Intelligence courses for professionals," in *Proceedings of then2020 IEEE Frontiers in Education Conference (FIE)*, pp. 1–5, IEEE, Uppsala, Sweden, October 2020.

[10] İ. Y. Kazu and Y. Issaku, "English language teaching students' perceptions on the concept of flipped classroom in teaching English: a metaphoric study," *Electronic Journal of Education Sciences*, vol. 9, no. 17, pp. 72–88.

[11] J. Liu, H. Bi, and M. Wang, "Using multi-source data to assess livability in Hong Kong at the community-based level: a combined subjective-objective approach," *Geography and Sustainability*, vol. 1, no. 4, pp. 284–294, 2020.

[12] Q. Zhang, B. Lian, P. Cao, Y. Sang, W. Huang, and L. Qi, "Multi-source medical data integration and mining for healthcare services," *IEEE Access*, vol. 8, pp. 165010–165017, 2020.

[13] F. H. Chen, "Sustainable education through E-learning: the case study of iLearn2. 0," *Sustainability*, vol. 13, no. 18, Article ID 10186, 2021.

[14] S. R. Hodge and P. Jansma, "Effects of contact time and location of practicum experiences on attitudes of physical education majors," *Adapted Physical Activity Quarterly*, vol. 16, no. 1, pp. 48–63, 1999.

[15] U. Sharma, C. Forlin, and T. Loreman, "Impact of training on pre-service teachers' attitudes and concerns about inclusive education and sentiments about persons with disabilities," *Disability & Society*, vol. 23, no. 7, pp. 773–785, 2008.

[16] L. J. Lieberman, C. Houston-Wilson, and F. M. Kozub, "Perceived barriers to including students with visual impairments in general physical education," *Adapted Physical Activity Quarterly*, vol. 19, no. 3, pp. 364–377, 2002.

[17] M. E. Stuart, L. Lieberman, and K. E. Hand, "Beliefs about physical activity among children who are visually impaired and their parents," *Journal of Visual Impairment & Blindness*, vol. 100, no. 4, pp. 223–234, 2006.

[18] S. Meegan and A. MacPhail, "Irish physical educators' attitude toward teaching students with special educational needs," *European Physical Education Review*, vol. 12, no. 1, pp. 75–97, 2006.

[19] S. L. Folsom-Meek, R. J. Nearing, W. Groteluschen, and H. Krampf, "Effects of academic major, gender, and hands-on experience on attitudes of preservice professionals," *Adapted Physical Activity Quarterly*, vol. 16, no. 4, pp. 389–402, 1999.

[20] A. R. Taliaferro and S. M. Bulger, "A delphi study of effective adapted physical education practicum experiences," *Adapted Physical Activity Quarterly*, vol. 37, no. 1, pp. 20–40, 2020.

[21] V. Suthakaran, S. Wright, E. Simpson, M. Marra, and D. Sonner, "The impact of information-processing styles on college students' attitudes toward people with disabilities," *Journal of Applied Rehabilitation Counseling*, vol. 42, no. 4, pp. 19–26, 2011.

[22] J. Lee, S. H. Chang, and J. A. Haegele, "Does service learning work? Attitudes of college students toward individuals with disabilities," *Journal of Experiential Education*, vol. 43, no. 4, pp. 365–380, 2020.

[23] S. Guo, G. Yang, T. Pei et al., "Analysis of factors affecting urban park service area in Beijing: perspectives from multi-source geographic data," *Landscape and Urban Planning*, vol. 181, pp. 103–117, 2019.

[24] V. H. Pedersen, P. Dagenais, and P. Lehoux, "Multi-source synthesis of data to inform health policy," *International Journal of Technology Assessment in Health Care*, vol. 27, no. 3, pp. 238–246, 2011.

[25] M. Garcia-Molsosa, J. Collet-Sabé, J. C. Martori, and C. Montserrat, "School satisfaction among youth in residential care: a multi-source analysis," *Children and Youth Services Review*, vol. 105, Article ID 104409, 2019.

[26] X. Wu, "The evaluation of the innovation teaching ability of physical education in Colleges and Universities under the regional difference," in *Proceedings of the 2017 International Conference on Robots & Intelligent System (ICRIS)*, pp. 346–349, IEEE, Huai An City, China, October 2017.

[27] D. Korzun and A. Meigal, "Multi-source data sensing in mobile personalized healthcare systems: semantic linking and data mining," in *Proceedings of the 2019 24th Conference of Open Innovations Association (FRUCT)*, pp. 187–192, IEEE, Moscow, Russia, April 2019.

[28] X. Zhu, C. D. Ennis, and A. Chen, "Implementation challenges for a constructivist physical education curriculum," *Physical Education and Sport Pedagogy*, vol. 16, no. 1, pp. 83–99, 2011.

[29] Z. Xu, D. Jia, and X. Cheng, "Research on criminal mental health risk assessment and intelligent correction system based on multi-source data fusion," *Design Engineering*, pp. 357–370, 2020.

[30] S. Liu, L. Zhang, Y. Long, Y. Long, and M. Xu, "A new urban vitality analysis and evaluation framework based on human activity modeling using multi-source big data," *ISPRS International Journal of Geo-Information*, vol. 9, no. 11, p. 617, 2020.