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Research on the Analysis of Exam Grades and Process Learning Data Based on SPSS

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Abstract: With the combination of education and information technology, online and offline hybrid teaching has become the new normal of college teaching. The addition of online platforms has had a profound impact on both teaching and learning sides. In recent years, learning data analysis based on online platforms has gradually become a hot topic in blended learning research. Through statistical analysis of individual learning data, the problems in the learning process can be identified and the teaching process can be optimized by targeted improvements. In this article, SPSS statistical software is used to analyze the quality of college physics course exam papers, combining the blended teaching practice in the 2022 mathematics major of Wuhan Textile University. The common knowledge weaknesses in the students were found. And by analyzing the correlation between final grades and the scores of the students' learning habits and chapter exercises, the blended teaching design of the course was reflected.

1. Introduction

College physics is a compulsory basic course for science and engineering majors in universities. As a fundamental natural discipline, college physics not only undertakes the task of knowledge learning, but also cultivates the students' comprehensive literacy such as scientific methods and logical reasoning, which plays an important leading role in their subsequent learning [1, 2]. In recent years, many universities in China have actively promoted blended learning reform based on online platforms, which has also provided a foundation for learning data analysis in evaluating students' learning outcomes [3]. Online platforms can record learners' process data, then the key factors that affect course performance can be obtained by analyzing these data. These analyses can provide important reference for teachers to optimize teaching [4]. Faced with hundreds or thousands of performance data in public courses, it is an urgent problem for teachers that how to improve work efficiency and obtain statistical results of student performance analysis [5, 6].

Statistical analysis methods, such as SPSS and Python, are effective tools to solve such problems. SPSS is the abbreviation for Statistical Program for Social Sciences. As a statistical analysis tool, it is widely used in various fields such as natural sciences, technical sciences, and social sciences [7].

The statistical function of SPSS includes all items in educational statistics, including descriptive statistics, correlation analysis, analysis of variance, t-test, etc[8]. It can achieve the analysis and calculation of various indicators in performance analysis, and play a good guiding role for teacher exam analysis and teaching work.

2. Subjects and Methods

In this paper, the online learning data and final grade data of the "College Physics" course at a certain university from 2022-2023-2 semesters are summarized. Based on SPSS 21.0, the basic information, difficulty and differentiation of test questions are researched. And the correlation between process learning and Final examination scores are also studied by the same software. The statistics and analysis of these learning data can be used for optimizing and reflecting on the course content and teaching organization.

Table 1 shows the final examination paper structure of the semester, in which the question types are multiple choice questions (MCQ), fill-in-the-blank questions (FIB) and calculation questions (Cal.). The distribution of the scores of the three question types is shown in the table.

Table 1: Test structure

Items	Marks
MCQ	24
FIB	16
Cal.	60

3. Results and Discussion

3.1. The Descriptive Statistical Analysis

The descriptive statistical analysis mainly includes the number of students (N), maximum and minimum values, mean value, median value, standard deviation and variance and so on, as shown in table 2.

Table 2: The descriptive statistics analysis

Class	N	Mean Score	Std. Deviation Score	Median	Maximum	Minimum	Variance
1	122	69.1066	15.19776	69.00	100	16	230.972

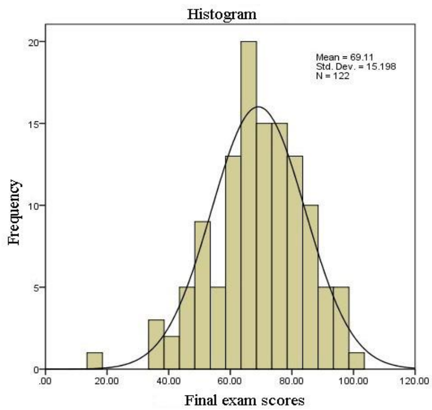

Figure 1: Distribution of final examination scores in Class 1

Figure 1 shows the normal distribution of the final exam scores of mathematics majors in 2022. According to table 2, the total number of the class students is 122, with an average score of 69.11 and the highest score of 100. The results basically conform to the Normal distribution. The lower average score due to the students' grades are mainly concentrated in the range of 70-85, with a relatively small proportion of students above 90. This also indicates that the excellent rate of the class needs to be improved.

3.2. Difficulty Analysis of the Test Paper

Difficulty analysis is an analysis of individual items in a measurement scale or test paper [9]. The difficulty coefficient is a quantitative measure of the difficulty degree encountered in answering a question, represented by the symbol P. Table 3 shows the evaluation indicators for the difficulty of the test questions.

Table 3: difficulty evaluation

Difficulty Coefficient(P)	Evaluation results
$P \geq 0.7$	Easy
$0.4 \leq P \leq 0.7$	Medium difficulty
$P \leq 0.4$	Difficulty

There are many methods for calculating the difficulty coefficient. In this article, the score rate is used as an indicator of the difficulty coefficient, and its calculation formula is:

$$P = \frac{X}{X_{\max}} \tag{1}$$

In the formula, P represents the difficulty of the question, while X represents the average score of the subject on a certain question, and X_{max} is the full score of the question.

It can be seen from Table 4 that the difficulty coefficient P of MCQ is 0.73, indicating that the MCQ is relatively easy. The difficulty levels for FIB and calculating questions are respectively 0.64 and 0.69, indicating that both questions are of moderate difficulty. The difficulty coefficient of each calculation question is also given in table 4 (the last six rows). It can be seen that the difficulty coefficient of the six questions is 0.85 at the highest and 0.57 at the lowest. The corresponding knowledge points are particle kinematics and thermal engine efficiency calculation. This result also indicates that the students have significant differences in their mastery of different knowledge points. In future teaching process, more attention should be paid to the learning difficulties associated with specific knowledge content.

Table 4: Analysis of difficulty coefficient of questions

Items	N	Mean Score	Whole Score	Difficulty Coefficient
MCQ	122	17.4098	24	0.73
FIB	122	10.1639	16	0.64
Calculation	122	45.4508	60	0.69
Calculation 1	122	8.5082	10	0.85
Calculation 2	122	6.2541	10	0.63
Calculation 3	122	7.5492	10	0.75
Calculation 4	122	7.3033	10	0.73
Calculation 5	122	6.1475	10	0.61
Calculation 6	122	5.6885	10	0.57

The overall difficulty of the test paper is moderate to easy. Considering that college physics adopted a unified examination and need to adapt to those students with different learning backgrounds, the difficulty of the test paper is relatively reasonable.

3.3. Differentiation Analysis of the Test Paper

Differentiation is an analysis of the discrimination of individual questions in a measurement scale or test paper [10]. The degree of differentiation reflects how well a test item differentiates between students' abilities. By analyzing the degree of differentiation of test questions, it is possible to better understand the distinction between students' actual ability levels.

The following method was used to calculate the differentiation [11]. Firstly, the scores were sorted, with P1=27% for the difficulty of the high group and P2=27% for the difficulty of the low group. Then the differentiation (D) is calculated by the formula:

$$D = (\text{average score of 27\% high group - average score of 27\% low group}) \div \text{full score value.}$$

Table 5: Independent sample T-test results

	Levene's Test for Equality of Variances		T-test for Equality of Means						
	F	Sig.	T	df	Sig. (2-tails)	Mean Difference	Std. error Difference	95% Confidence Interval of the Difference	
								Lower	upper
MCQ	6.321	.014	14.810	66	.000	24.20588	1.63438	20.94274	27.46903
			14.810	52.160	.000	24.20588	1.63438	20.92650	27.48527
FIB	.394	.532	7.379	66	.000	5.47059	.74142	3.99030	6.95088
			7.379	63.565	.000	5.47059	.74142	3.98924	6.95194
Cal.	3.520	.065	8.976	66	.000	6.05882	.67498	4.71119	7.40646
			8.976	58.930	.000	6.05882	.67498	4.70816	7.40948

The differentiation analysis of the test paper is also conducted and the results are shown in the table 5. Levene's test for equal variance is the homogeneity of variance test. If the probability P-value corresponding to the homogeneity of variance test is greater than the significance level of 0.05, it indicates that there is no significant difference in variance. Therefore, it should be based on the T-test results of the assumed equal number of variables in the first row. From Table 5, it can be seen that the probability P-values corresponding to the homogeneity test of variance are all greater than the significance probability level of 0.05, indicating that there is no significant difference in variance. Therefore, the T-test results in the first row should be considered. The probability P value corresponding to the single Multiple choice questions, the blank filling questions and the calculation questions are equal to 0.000, indicating that there have a high degree of discrimination in these questions of the test.

3.4. Analysis of the Correlation between Learning Data and Final Exam Grades

This semester, the course of college physics adopted a blended online and offline teaching approach. Multiple process learning data was recorded based on the online platform, including learning behavior, chapter exercises, interactive Q&A, and so on. The platform provided the learning habit scores by calculating individual students' learning behavior data, such as learning duration, learning frequency and duration in a certain proportion. And the learning habit scores were used to reflect the students' process learning status. Here, a preliminary analysis was conducted on the correlation between the exam grades and the scores of learning habits and chapter exercises. The Pearson correlation analysis method was used, and the correlation coefficient r was calculated using the formula:

$$r = \frac{\sum_{i=1}^{n}(X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^{n}(X_i - \bar{X})^2}\sqrt{\sum_{i=1}^{n}(Y_i - \bar{Y})^2}} \tag{2}$$

In table 6, the correlation analysis results had been presented between learning habit scores, chapter exercise scores, and final exam scores. The results showed that there was a correlation between chapter exercises and final examination scores, while there was no obvious correlation between learning habit scores and final scores. However, the learning habit scores were positively correlated with chapter exercises. Further analysis also found a negative correlation between learning habit scores and final grades in the 0-60 score range. Through interviews with these students, it was found that the mainly reason was that these students had poor learning foundation. Although they put in more time to complete online learning tasks, they still cannot achieve ideal scores in final examination. For this group of students, incorporating learning habits into their regular grades can provide good encouragement and promotion. Similar situations also exist between 80-100 points. And the reason for this result was that the majority of the students in this score range had usually completed all the content in the classroom, which meant the dependence on online platforms of these students was weak. Then for these students, their learning habit scores determined by the platform were at a lower level because they had relatively little online learning data, such as learning duration and frequency. The results also fully demonstrated the complexity of the interaction between various learning behaviors in blended learning.

Table 6: The correlation analysis between process data and exam grades

		Learning habits	Chapter assignments	Exam score
Learning habit scores	Pearson Correlation	1	.231*	.131
	Sig. (2-tailed)		.010	.149
	N	122	122	122
Chapter exercise scores	Pearson Correlation	.231*	1	.354**
	Sig. (2-tailed)	.010		.000
	N	122	122	122
Exam score	Pearson Correlation	.131	.354**	1
	Sig. (2-tailed)	.149	.000	
	N	122	122	122

*. Correlation is significant at the 0.05 level (2-tailed).

**. Correlation is significant at the 0.01 level (2-tailed).

4. Conclusion

Based on the SPSS software, statistical analysis was conducted on the grades of a university physics course in a certain semester, including basic information on the test paper, difficulty and differentiation analysis, and correlation analysis between process data and grade data. The results indicate that the overall difficulty of the course exam questions is moderate and the differentiation is reasonable. At the same time, it is also found that students have certain difficulties in learning and mastering some knowledge content. The results of SPSS analysis are beneficial for teachers to reflect and summarize their teaching, and provide effective data support for course design and optimization in subsequent teaching.

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