DOI: 10.66069/ojspub.1137261013

An Empirical Study on the Application of AI-based Student Layered Profiling in Teaching International Trade Principles

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Abstract: ***This research takes layered profiling of 116 Business English majors in Principles of International Trade course from Xuexitong platform, together with students' grade sheet of this course as data sources, explores the correlation between composite score, learning ability from Xuexitong and regular grade, final grade, overall grade from grade sheet. Spearman correlation analysis conducted by SPSS software reveals that there is a significant positive correlation between composite score and regular grade, overall grade, between learning ability and regular grade, overall grade. The study also discovers that there is no significant correlation between composite score and final grade, between learning ability and final grade. This indicates that students' online learning profiling reflects process-based performance and cannot predict the outcomes of final assessments. Since regular grades are partially derived from online learning behaviors, process-based profiling is positively correlated with regular grade and overall grade. The paper proposes that layered profiling can drive pedagogical reflection and teaching improvement, facilitate students' autonomous learning, enable teachers to identify different groups of students, and lay a foundation for differentiated instruction.***

Keywords: Student layered profiling, Teaching, International Trade Principles, Spearman correlation analysis, Xuexitong.

1. Introduction

Principles of International Trade is a core foundational course for Business English majors. It aims to help students build a basic theoretical framework for the international exchange of goods and services, understand the formation logic of trade policies and their economic effects, and develop the ability to analyze real trade phenomena with theory. The course is characterized by abstract theory, rapidly updated policies, and students differ markedly in their high-school foundations, study habits, and self-learning ability, posing practical challenges to a uniform paced classroom.

In recent years, online teaching platforms represented by Xuexitong have accumulated massive learning-behavior data of students. Relying on machine learning and statistical modeling, such platforms can automatically generate multi-dimensional student layered profiles, turning an amorphous class into identifiable and intervenable tiers, which makes precise instruction and process-oriented assessment possible. Yet the statistical relationship between the online learning performance depicted by the profiles (learning ability, composite score, and so on) and the final course grades remains to be quantitatively tested for stability.

This study, based on the real data of 116 students of International Trade Principles course, pursues two lines of inquiry. First, using SPSS we clarify the distribution shape of the core variables and thereby select an appropriate correlation method. Second, through Spearman correlation analysis we empirically examine the relationship between students' online learning profiles (learning ability, composite score) and the course regular grade, final grade and overall grade. Finally, we link the quantitative conclusions with the instructional application of AI layered profiling, to systematically elaborate its application and value in teaching Principles of International Trade.

2. Data Sources and Research Methods

2.1 Data Sources

The data come from two sources. One is Xuexitong APP, which records 116 Business English majors' online learning duration, composite score, learning efficiency and learning ability in International Trade Principles course. The other is students' Grade Sheet of this course, including regular grade, final grade and overall grade.

1) According to the data from Xuexitong APP, 116 students are divided into four tiers: All-Round Excellence, Academic Top, Diligent, and Need of Improvement.

In the tables below, data of the two original classes (Class 1 and Class 2) have been merged. No. 1-58 belong to Class 1, and No. 59-116 belong to Class 2. A student's composite score is the weighted sum of two parts: Class Participation (10%, maximum 10 points) and Course Points (90%, maximum 90 points), giving a full score of 100.

All-Round Excellence

Stratification criterion: both composite score and online learning duration exceed the class average (Class 1: average composite score 94.2, average learning duration 84.85 minutes; Class 2: average composite score 89.37, average learning duration 79.81 minutes).

35 students, accounting for 30.17% (17 from Class 1, 18 from Class 2).

Table 1: All-Round Excellence tier (35 students)

No.	Online Duration (min)	Composite Score	Learning Efficiency (Composite / Duration)	Learning Ability (Composite× 0.6 + Duration× 0.4)
1	114.2	99.33	0.87	96.97
2	100.3	99.33	0.99	97.33
3	156.6	99.33	0.63	98.08

4	237.5	99.33	0.42	103.77
5	168.3	96.88	0.58	95.97
6	88.3	96.88	1.09	95.97
7	120.9	99.33	0.82	97.73
8	95.1	99.33	1.04	97.33
9	150.0	99.33	0.66	98.08
10	101.7	99.33	0.98	97.33
11	166.9	99.33	0.59	98.08
12	172.3	99.33	0.58	98.08
13	110.1	97.55	0.88	95.97
14	145.4	99.33	0.68	98.08
15	121.5	98.51	0.81	96.97
16	157.0	97.69	0.62	96.97
17	98.8	96.88	0.98	95.97
59	83.5	92.78	1.11	88.68
60	148.1	99.33	0.67	96.33
61	84.0	99.33	1.18	95.33
62	122.8	89.67	0.73	86.67
63	85.4	98.0	1.15	93.4
64	333.5	99.33	0.29	113.33
65	205.8	99.33	0.48	103.33
66	103.0	98.51	0.96	95.51
67	97.3	99.33	1.02	96.33
68	84.1	94.42	1.12	89.42
69	98.0	96.06	0.98	94.06
70	145.2	99.33	0.68	96.33
71	81.3	96.88	1.19	93.88
72	110.6	95.55	0.86	92.55
73	80.3	89.67	1.12	86.67
74	106.3	99.33	0.93	95.33
75	85.0	98.67	1.16	95.67
76	92.9	99.33	1.07	96.33

Academic Top

Stratification criterion: composite score exceeds the average, but online learning duration does not exceed the average.

47 students, accounting for 40.52% (26 from Class 1, 21 from Class 2).

Table 2: Academic Top tier (47 students)

No.	Online Duration (min)	Composite Score	Learning Efficiency (Composite / Duration)	Learning Ability (Composite× 0.6 + Duration× 0.4)
18	54.9	99.33	1.81	98.13
19	81.3	99.33	1.22	96.33
20	60.0	99.33	1.66	95.33
21	82.3	96.88	1.18	94.88
22	12.4	96.88	7.81	58.98
23	71.0	99.33	1.39	95.33
24	71.3	98.67	1.38	95.67
25	81.1	96.88	1.19	94.88
26	33.8	94.42	2.79	59.12
27	56.3	99.33	1.76	95.33
28	65.5	94.58	1.45	91.58
29	71.6	98.67	1.38	95.67
30	61.8	99.33	1.61	95.33
31	71.4	96.88	1.36	94.88
32	84.3	99.33	1.18	95.33
33	67.8	99.33	1.46	95.33
34	60.5	99.33	1.64	95.33
35	79.4	99.33	1.25	95.33
36	81.6	98.51	1.21	95.61
37	52.1	97.85	1.88	94.15
38	49.9	96.88	1.94	93.88
39	74.7	99.33	1.33	95.33
40	48.0	98.51	2.05	94.51
41	84.0	99.33	1.18	95.33
42	62.5	94.42	1.51	91.42
43	81.7	96.88	1.19	94.88
77	64.4	92.78	1.44	89.78
78	70.0	99.33	1.42	95.33
79	51.0	93.6	1.84	89.6
80	54.0	98.67	1.83	95.67
81	53.1	97.33	1.83	94.33
82	65.9	99.33	1.51	95.33
83	75.0	99.33	1.33	95.33
84	64.9	97.69	1.51	94.69
85	73.7	100.0	1.36	98.0
86	71.5	92.78	1.29	89.78
87	66.0	95.55	1.45	92.55
88	73.5	92.78	1.26	89.78
89	56.9	97.18	1.71	93.18
90	50.0	90.33	1.81	85.33
91	71.4	99.33	1.39	95.33
92	51.2	94.42	1.84	89.42
93	46.1	98.0	2.13	94.0
94	51.7	93.76	1.81	89.76
95	53.7	99.33	1.85	95.33
96	77.8	98.51	1.27	95.51
97	53.2	93.76	1.76	89.76

Diligent

Stratification criterion: online learning duration exceeds the average, but composite score is below the average.
6 students, accounting for 5.17% (2 from Class 1, 4 from Class 2).

Table 3: Diligent tier (6 students)

No.	Online Duration (min)	Composite Score	Learning Efficiency (Composite / Duration)	Learning Ability (Composite× 0.6 + Duration× 0.4)
44	85.3	92.12	1.08	89.08
45	99.9	76.42	0.77	82.02
98	82.0	80.36	0.98	83.36
99	88.0	83.78	0.95	85.98
100	88.6	85.58	0.97	86.58
101	104.5	88.03	0.84	89.03

Need of Improvement

Stratification criterion: neither composite score nor online learning duration exceeds the average.

28 students, accounting for 24.14% (13 from Class 1, 15 from Class 2).

Table 4: Need of Improvement tier (28 students)

No.	Online Duration (min)	Composite Score	Learning Efficiency (Composite / Duration)	Learning Ability (Composite× 0.6 + Duration× 0.4)
46	64.7	92.78	1.43	83.78
47	64.0	90.33	1.41	82.33
48	50.0	92.78	1.86	83.78
49	51.0	92.78	1.82	83.78
50	50.6	46.97	0.93	48.17
51	74.5	92.78	1.25	83.78
52	42.0	92.78	2.21	83.78
53	55.1	93.76	1.70	84.76
54	55.7	93.76	1.68	84.76
55	68.2	83.78	1.23	80.78
56	48.2	43.69	0.91	45.69
57	64.1	88.69	1.38	85.69
58	42.0	64.15	1.53	58.15
102	21.3	68.24	3.20	50.24
103	71.2	80.51	1.13	77.51
104	30.9	80.67	2.61	65.67
105	74.3	88.03	1.19	81.03
106	58.0	77.4	1.33	70.4
107	74.3	75.76	1.02	74.76
108	66.5	83.78	1.26	78.78
109	42.0	71.67	1.71	63.67
110	63.0	83.27	1.32	78.27
111	39.0	80.15	2.06	65.15
112	24.0	39.6	1.65	43.6

113	51.0	64.82	1.27	57.82
114	73.8	38.27	0.52	50.27
115	54.8	55.31	1.01	50.31
116	79.8	89.36	1.12	83.36

2) Grade Sheet includes regular grade, final grade and overall grade of International Trade Principles course. Regular grade covers class participation, group activities and course points (homework plus interaction). Final grade covers group presentation and learning reflection. Overall grade is computed as: overall grade = regular grade × 0.4 + final grade × 0.6.

Table 5: Grade Sheet of International Trade Principles course

No.	Regular Grade	Final Grade	Overall Grade
1	97.6	93.3	95
2	97.6	92.6	95
3	98.5	92.1	94.8
4	99.4	89.9	93.6
5	97.5	91.4	93.8
6	97.5	92.1	94.4
7	97	91.3	93.4
8	98.5	93.5	96
9	97	94.1	95.2
10	97	90.6	93.4
11	98.5	92.1	94.8
12	97.6	94	95.6
13	97	90.6	93.4
14	97.6	90	93.2
15	96.5	87.9	91.6
16	97	90	92.8
17	96	89.9	92.4
59	98.2	90.4	93.2
60	97.6	91.5	94.4
61	97	91.4	93.4
62	96.4	91.5	93.6
63	95.8	89.4	91.8
64	97	92.7	94.6
65	98.2	91.1	93.8
66	98.2	88.7	92.6
67	94.3	91.4	92.2
68	97	91.4	93.4
69	97	89.3	92.2
70	97.6	92.8	95
71	97	94.2	95.2
72	94.6	94.2	94.4
73	95.3	90	92
74	97	93.4	94.6
75	96.4	92.8	94.2
76	98.2	92.9	95
18	97	93.3	94.6
19	97	89.8	92.8
20	97	91.2	93.4
21	98.4	91.3	93.8
22	98.4	90.6	93.8
23	99.4	90.6	94.2
24	94.9	91.2	92.6
25	94.5	89.3	91.4
26	96	92.1	93.6
27	98	91.4	93.8
28	95.3	92.1	93.2
29	97.3	91.4	93.4
30	97.6	95.4	96.2
31	96.6	90.9	93.4
32	98.5	88.6	93
33	97.6	92.8	95
34	97.6	85.8	90.8
35	97.6	90	93.2
36	96.5	92.8	94.6
37	93.8	89.2	91
38	96.6	89.5	92.8
39	97	87.9	91.6
40	97.6	90	93.2
41	97.6	90	93.2
42	93.5	88.3	90.4
43	96.6	90.2	92.8
77	96.7	89.7	92.8
78	95.1	88	90.8
79	96	92.2	93.6
80	97	89.7	92.8
81	93.4	91.5	92.4
82	97	95	95.8
83	97	90.8	93.4
84	98.2	91.8	94.4
85	98.2	91.1	93.8
86	96	90.6	93
87	94.6	90	92
88	96	90	92.4
89	94.2	92.8	93.4
90	97.7	89.7	93.2
91	97.6	90	93.2
92	97	90.9	93.4
93	94.6	90.9	92.6
94	93.8	92.3	92.8
95	98.2	88.7	92.6
96	98.2	93.2	95
97	96	92.9	94.2
44	94.8	92.6	93.8
45	94	92.1	92.8
98	98.2	89.7	93.2
99	95.7	89	91.8
100	95.8	90.7	93
101	94.8	92	93.2
46	96.9	92.7	94.6
47	95	94.1	94.4
48	95.6	91.2	93
49	94.6	91.6	93.2
50	85	87.2	86.2
51	94.6	92.3	93.2
52	91.5	91.3	91.4
53	93.8	90.6	92.2
54	92.3	92	92
55	91.5	91.8	92
56	78.6	89.5	85.6
57	96.4	90.6	93
58	89.5	88.6	89.4
102	85.7	88.3	87.2
103	93	92.9	93
104	93.3	90.8	91.8
105	93.3	91.4	91.8
106	88.4	92.2	90.4
107	91	87.1	88.6
108	95	89.9	92
109	93.8	92.8	93.4
110	94.6	92.8	93.8
111	91.6	94.2	93.2
112	77	90.7	85.4
113	86	93	90.2
114	74.6	90	84
115	96.4	90.7	93
116	97.6	90.8	93.8

Serial numbers 1 to 116 in Table 5 keep the consistent order with the serial numbers in Table1-4, ensuring the validity of subsequent statistical pairing.

2.2 Research Variables

This study selects five variables as the objects of analysis:

Learning Ability: from Student Layered Profiling, comprehensively reflecting students' knowledge mastery and high-level thinking. It is computed as: learning ability = composite score × 0.6 + online learning duration× 0.4.

Composite Score: from Student Layered Profiling, a

comprehensive quantification of students' regular performance.

Regular Grade: from the Grade Sheet, regular grade covers class participation, group activities and course points (homework plus interaction), representing the process-oriented assessment component.

Final Grade: from the Grade Sheet, final grade covers group presentation and learning reflection, representing the summative assessment result.

Overall Grade: from the Grade Sheet, overall grade = regular grade × 0.4 + final grade × 0.6, representing the comprehensive final result.

2.3 Research Methods

1) Normality test — Input the above five variables into SPSS software and make Kolmogorov-Smirnov Tests to determine whether these five variables are normally distributed or not.

2) Spearman correlation analysis — When normality is violated, the nonparametric Spearman correlation analysis is adopted.

3. Results and Analysis of the Normality Test

Five variables in Table 1-5 — learning ability, composite score, regular grade, final grade, overall grade — are input into SPSS Statistics system. We make Kolmogorov-Smirnov Tests to determine whether these five variables are normally distributed or not. We can get the following results by K-S test:

Table 6: Nonparametric Tests

Hypothesis Test Summary				
	Null Hypothesis	Test	Sig.	Decision
1	The distribution of Composite Score is normal with mean 91.78 and standard deviation 12.66440.	One-Sample Kolmogorov-Smirnov Test	0.000[a]	Reject the null hypothesis.
2	The distribution of Learning Ability is normal with mean 88.01 and standard deviation 13.45650.	One-Sample Kolmogorov-Smirnov Test	0.000[a]	Reject the null hypothesis.
3	The distribution of Regular Grade is normal with mean 95.35 and standard deviation 4.02351.	One-Sample Kolmogorov-Smirnov Test	0.000[a]	Reject the null hypothesis.
4	The distribution of Final Grade is normal with mean 91.11 and standard deviation 1.75479.	One-Sample Kolmogorov-Smirnov Test	0.200[a,b]	Retain the null hypothesis.
5	The distribution of Overall Grade is normal with mean 92.87 and standard deviation 2.02836.	One-Sample Kolmogorov-Smirnov Test	0.000[a]	Reject the null hypothesis.

Asymptotic significances are displayed. The significance level is 0.050.
a. Lilliefors Corrected
b. This is a lower bound of the true significance.

From Table 6, we can find that Final Grade of International Trade Principles course is normally distributed because the level of significance is more than 0.05 (p=0.2>0.05). We can also find that Composite Score, Learning Ability, Regular Grade, Overall Grade are not normally distributed because the level of significance is less than 0.05 (p=0.000<0.05).

This research focuses on making a correlation analysis on Composite Score and Regular Grade, Final Grade, Overall Grade, making a correlation analysis on Learning Ability and Regular Grade, Final Grade, Overall Grade. The above five groups of data are independent variables, and all these five variables can be measured at the interval level, but four of these five variables are not normally distributed, so we should make Spearman correlation analysis to decide whether there is a significant positive correlation between Composite Score and Regular Grade, Final Grade, Overall Grade, and also decide whether there is a significant positive correlation between Learning Ability and Regular Grade, Final Grade, Overall Grade of International Trade Principles course.

4. Results and Analysis of Spearman Correlation

4.1 Research Hypotheses

According to the above data in Table1-5, our question is whether Composite Score and Regular Grade, Final Grade, Overall Grade are significantly correlated or not, and whether Learning Ability and Regular Grade, Final Grade, Overall Grade are significantly correlated or not. In another word, is there a relationship between Composite Score and Regular Grade, Final Grade, Overall Grade? Is there a relationship between Learning Ability and Regular Grade, Final Grade, Overall Grade? According to these questions, we are conducting the following hypothesis test:

Null hypothesis H_0: $\rho = 0$
Research hypothesis H_1: $\rho \neq 0$

Null hypothesis in this research is that there is no correlation on Composite Score and Regular Grade, Final Grade, Overall Grade, there is no correlation on Learning Ability and Regular Grade, Final Grade, Overall Grade.

Research hypothesis here is that Composite Score and Regular Grade, Final Grade, Overall Grade are correlated, Learning Ability and Regular Grade, Final Grade, Overall Grade are correlated.

By using SPSS Statistics system, we can get Spearman Correlation coefficient of these variables respectively. If the absolute value of the correlation coefficient is between 0.3 and 0.7, there is a moderate correlation; being less than 0.3 indicates low correlation; being greater than 0.7 indicates high correlation. We set the significance level at≤0.05. If significance level p is equal to or less than 0.05, we reject the null hypothesis and accept the research hypothesis; if significance level p is more than 0.05, we accept the null hypothesis. (Xu Hongchen, 2013:64)

4.2 Results

Input the above five variables ---Composite Score, Learning Ability, Regular Grade, Final Grade, Overall Grade in Table1-5 into SPSS software, then we employ Spearman correlation analysis and a two-tailed test of significance. See Table 7 for the results:

Table 7: Nonparametric Correlations

Correlations							
			Composite Score	Learning Ability	Regular Grade	Final Grade	Overall Grade
Spearman's rho	Composite Score	Correlation Coefficient	1.000	0.901**	0.693**	0.098	0.490**
		Sig. (2-tailed)	.	0.000	0.000	0.294	0.000
		N	116	116	116	116	116
	Learning Ability	Correlation Coefficient	0.901**	1.000	0.661**	0.106	0.489**
		Sig. (2-tailed)	0.000	.	0.000	0.256	0.000
		N	116	116	116	116	116
	Regular Grade	Correlation Coefficient	0.693**	0.661**	1.000	0.026	0.637**
		Sig. (2-tailed)	0.000	0.000	.	0.779	0.000
		N	116	116	116	116	116
	Final Grade	Correlation Coefficient	0.098	0.106	0.026	1.000	0.709**
		Sig. (2-tailed)	0.294	0.256	0.779	.	0.000
		N	116	116	116	116	116
	Overall Grade	Correlation Coefficient	0.490**	0.489**	0.637**	0.709**	1.000
		Sig. (2-tailed)	0.000	0.000	0.000	0.000	.
		N	116	116	116	116	116

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

4.3 Discussion

The above Table 7 shows the Spearman correlation coefficient (ρ= 0.693), significance level (p = 0.000) and number of the subjects (n = 116) for Composite Score and Regular Grade, the Spearman correlation coefficient (ρ= 0.098) and significance level (p = 0.294) for Composite Score and Final Grade, the Spearman correlation coefficient (ρ= 0.490) and significance level (p = 0.000) for Composite Score and Overall Grade.

Table 7 also shows the Spearman correlation coefficient (ρ= 0.661), significance level (p = 0.000) and number of the subjects (n = 116) for Learning Ability and Regular Grade, the Spearman correlation coefficient (ρ= 0.106) and significance level (p = 0.256) for Learning Ability and Final Grade, the Spearman correlation coefficient (ρ= 0.489) and significance level (p = 0.000) for Learning Ability and Overall Grade.

1) There is a significant moderate correlation between Composite Score and Regular Grade (ρ= 0.693, p<0.05), between Composite Score and Overall Grade (ρ= 0.490, p<0.05). There is a significant moderate correlation between Learning Ability and Regular Grade (ρ= 0.661, p<0.05), between Learning Ability and Overall Grade (ρ= 0.489, p<0.05). Since the regular grade partly derives from online learning behavior and regular performance accounts for 40% of the overall grade, the significant positive correlation between process profiles and the overall grade is statistically self-consistent and reasonable.

2) There is no significant correlation between Composite Score and Final Grade (p>0.05), and no significant correlation between Learning Ability and Final Grade (p>0.05). This suggests that students' online learning profiles (process performance) cannot linearly predict their final grade; the final assessment is a relatively independent summative assessment.

5. The Application and Value of AI-based Student Layered Profiling in Teaching

5.1 Construction and Distribution of Layered Profiling

Student layered profiling is the outcome of clustering and labeling students from dimensions such as learning engagement, knowledge mastery, ability level, and learning efficiency, based on online learning process data. Using the two core dimensions — composite score and online learning duration, this course automatically assigns the 116 students to four tiers. The criteria and distribution are shown in Table 8.

Table 8: Classification criteria and distribution of the four profiling tiers

Tier	Criterion	Number of Students	Share %
All-Round Excellence	Both composite score and online learning duration above average	35	30.17
Academic Top	Composite score above average, online learning duration below average	47	40.52
Diligent	Online learning duration above average, composite score below average	6	5.17
Need of Improvement	Both composite score and online learning duration below average	28	24.14
Total		116	100

Average composite score is 94.2 and average learning duration is 84.85 minutes in Class 1; average composite score is 89.37 and average learning duration is 79.81 minutes in Class 2.

This stratification makes teachers see each group even in large classes, providing objective support for differentiated instruction.

5.2 Core Value of Layered Profiling in Teaching

1) Layered profiling supports precise and differentiated instruction. The one-size-fits-all teaching model struggles to accommodate advanced and underperforming students. Stratified student profiles enable teachers to assign research tasks (such as writing trade-policy commentaries) to students at All-Round Excellence tier, focus on method transfer for Academic Top tier, identify learning method issues and knowledge gaps for Diligent tier (high input but lower output), and provide timely intervention for students at Need of Improvement tier, shifting teaching from experience-driven to data-driven.

2) Layered profiling strengthens process-oriented assessment to compensate for the limitations of summative assessment alone. Traditional teaching often relies solely or primarily on final examination scores, which fail to reflect learners' real effort and sustained progress. Stratified profiles incorporate online learning duration, attendance, in-class activities, course points, group presentations and learning reflections into assessment throughout the teaching process. Empirical findings of this study further support this point: learning ability and composite score show a significant positive correlation with overall grade, yet no correlation with final

grade. This indicates that process-based profiles capture effective input of learning, validates the necessity of process-oriented assessment.

3) Layered profiling can provide academic early warning and targeted support. Identifying the Need of Improvement tier is essentially a forward-looking early-warning mechanism. When indicators such as online learning duration, activity participation remain persistently low, the system can promptly alert teachers to provide one-on-one tutoring and in-process intervention.

4) Layered profiling optimizes teaching resource allocation and group collaborative learning. Profiles provide objective evidence for classroom grouping and project-based learning. Heterogeneous grouping can be adopted to allow Top tier students to support Improvement tier learners, while homogeneous grouping can facilitate seminars. Meanwhile, it also helps teachers prioritize limited Q&A time.

5) Layered profiling promotes students' self-awareness and autonomous learning. When profiles are fed back to students themselves, it strengthens self-monitoring awareness, sparks intrinsic motivation, and pushes the shift from being taught to self-driven learning.

5.3 Mechanism of Xuexitong's AI-based Layered Profiling

Xuexitong is a widely used online teaching platform in universities. Its AI-based student layered profiling relies on the platform's learning-behavior data, automatically generating multi-dimensional labels through modeling and clustering, and directly serving lesson preparation, teaching, tutoring, and assessment. The mechanism can be summarized into three layers. First, a data-collection layer automatically records attendance check-in, online learning duration, class activities, course points, chapter quizzes, and resource access. Second, a profile-modeling layer uses machine learning and statistical modeling to turn raw data into interpretable labels such as learning ability, composite score, learning efficiency and so on. Third, a teaching-application layer establishes a cycle of pre-class diagnosis, in-class discussion, after-class targeted tutoring, assessment and feedback. Process data contributes to overall grades. This mechanism is already implementable and replicable in this course.

6. Conclusion

Normality tests show that four variables — Composite Score, Learning Ability, Regular Grade, Overall Grade — do not follow normal distribution, only one variable Final Grade is normally distributed. Therefore, nonparametric Spearman correlation analysis was adopted. Spearman analysis demonstrates that students' composite score and learning ability have no significant correlation with final grade, but show a moderate significant positive correlation with regular grade and overall grade. This means process assessment captured by online learning behaviors cannot be replaced by final assessment; it contributes substantively to overall grade and should serve as a basis for learning evaluation. This statistically validates the rationality of leveraging AI profiles to support process assessment and stratified teaching. AI-based student layered profiling can be used to support precise and differentiated instruction, enabling teaching improvement.

References

[1] Han Baocheng. Statistics in Foreign Language Teaching and Research [M]. Beijing: Foreign Language Teaching and Research Press, 2000.
[2] Robert Ho. Handbook of Univariate and Multivariate Data Analysis and Interpretation with SPSS [M]. Boca Raton: Taylor & Francis Group, 2006.
[3] Ronald D. Yockey, translated by Hu Qiang. SPSS Demystified (The Third Edition) [M]. Beijing: China Renmin University Press, 2019.
[4] Xu Hongchen. Learning Statistics from Examples of Second Language Research [M]. Beijing: Foreign Language Teaching and Research Press, 2013.
[5] Xu Hongchen. Statistical Analysis in English Language Teaching [M]. Beijing: Foreign Language Teaching and Research Press, 2023.