Effects of Data-Driven Online Teaching Process Optimization on Vocational College Students' Acquisition of Professional Skills in the Age of Digital Intelligence

Qin Zhong[1,2]

[1]Chongqing Business Vocational College, School of Digital Media, Chongqing, 401331, China
[2]Shinawatra University, Doctor of Philosophy Education Faculty of Education, Mueang pathum thani, Thailand

1024648383@qq.com

Abstract. Data-driven optimization of the online teaching process is achieved through real-time monitoring of learning situations and dynamic adaptation of resources, aiming to enhance the practicality and job-fit of vocational students' professional skills. This project takes data-driven optimization of the online teaching process as the independent variable and the acquisition effect of vocational students' professional skills as the dependent variable. Through data collection and analysis techniques, personalized teaching strategy adjustments, multi-modal resource development and intelligent adaptation, and the reconfiguration of teaching management processes, it directly acts on the analysis of the students' skill acquisition process. It quantitatively tracks the level of professional skills mastered by vocational students, their career competitiveness, and their ethical awareness, and concludes that data-driven precise, personalized, and scenario-based teaching intervention significantly improves the accuracy and practicality of vocational students' professional skills training. However, it requires multi-dimensional collaboration of technology, organization, and ethics to break through bottlenecks such as data silos and humanistic deficiencies.

Keywords: Age of Digital Intelligence, Data-Driven Online Teaching Process Optimization, Vocational College Students, Acquisition of Professional Skills

1 Introduction

Online teaching, as the core scenario of educational digital transformation, has advanced from the stage of "technology tools assisting" to the rapidly developing stage of "data-driven reconfiguration". Higher vocational education, as the core carrier for cultivating technical and skilled talents, its combination with online teaching is not only an inevitable trend of digital transformation but also a solution to the pain points of traditional vocational education. Integrating data-driven and online teaching organically is extremely urgent. This research is based on the new technologies of the digital intelligence era, focusing on "data-driven optimization of online teaching process", reconfiguring the teaching process through big data and artificial intelligence tech-

H. Kannan et al. (eds.), *Proceedings of the 5th International Conference on Internet, Education and Information Technology (IEIT 2025)*, Atlantis Highlights in Social Sciences, Education and Humanities 40,
https://doi.org/10.2991/978-94-6463-803-5_77

nologies, enhancing the practicality, job adaptability and learning efficiency of vocational students' professional skills, and promoting the improvement of the efficiency of skill talent cultivation.

1.1 Problem Statement

1.1.1 Problem Statement of Vocational Students' Acquisition of Professional Skills.

The acquisition of professional skills by vocational college students involves core dimensions such as curriculum The acquisition of professional skills by vocational college students involves core dimensions such as curriculum system design, implementation of practical teaching, depth of industry-academia integration, and students' sense of career identity. Firstly, there is a disconnection between curriculum design and industrial demands. Secondly, the effectiveness of practical teaching is insufficient. Thirdly, the teaching ability and teaching methods of the teaching staff tend to be traditional. Fourthly, vocational college students' sense of career identity and learning motivation are insufficient.

1.1.2 Problem Statement on Data-driven Online Teaching Process Optimization in Higher Vocational Education.

At present, data applications are mostly confined to the teaching management level (such as attendance checking and homework submission), and have not yet formed a closed-loop teaching optimization mechanism of "data collection - analysis - intervention". Firstly, there is a disconnection between large-scale online teaching and individualized demands. Secondly, teachers and students lack the motivation to explore and apply online teaching data. Thirdly, data-driven online teaching involves ethical and fairness risks.

1.2 Problem Statement

1.2.1 How is the Situation of Data-Driven Online Teaching Process Optimization in Higher Vocational Colleges?

1.2.2 What professional skills do higher vocational students need to acquire?

1.2.3 Is the Data-driven Online Teaching Process Optimization Necessary for Higher Vocational Students to Acquire Professional Skills?

1.2.4 How can Data-driven Online Teaching Process Optimization Promote Higher Vocational Students to Acquire Professional Skills?

1.3 Research Objectives

1.3.1 To Research on Data-Driven Online Teaching Process Optimization in Higher Vocational Colleges.

1.3.2 To research on Professional Skills Acquisition by Higher Vocational Students.

1.3.3 To research on the Impact of Data-driven Online Teaching Process Optimization in Higher Vocational Colleges on Professional Skills Acquisition by Higher Vocational Students.

1.3.4 To rut Forward Suggestions and Opinions for Strengthening Higher Vocational Students' Efficient and Accurate Acquisition of Professional Skills Through Online Teaching.

1.4 Conceptual Framework

as shown in figure 1.

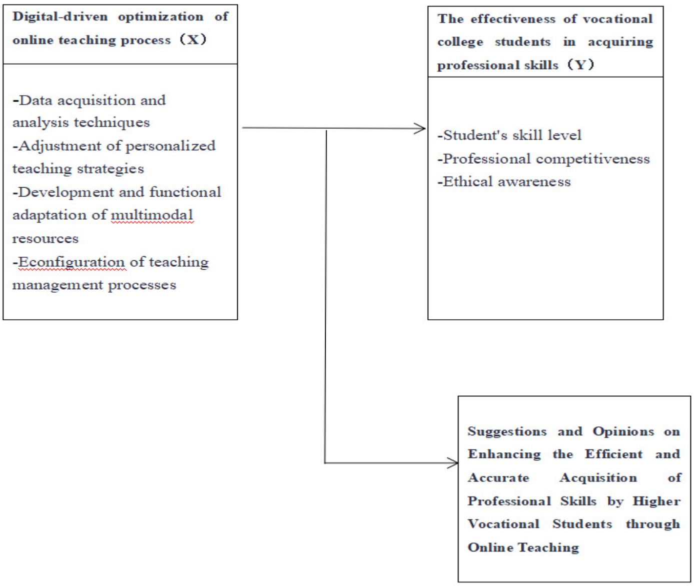

Fig. 1. Conceptual Framework

2 Literature Review

Gu, M., Y.,(2018) [1]The digital transformation of education has become an important trend in educational reform in the digital intelligence era. Under the background of digital transformation, many changes have occurred in education. Zhu, Z., T. (2022)[2] In the digital intelligence era, the application of digital technology, virtual space and data management provides support for the construction and development of smart environment, smart teaching methods and smart evaluation, thereby promoting the practice of educational digital transformation. Wuhan University (2024)[3] uses large model to analyze student question data and accurately locate teaching blind spots. Shanghai Business Foreign Language School (2022)[4] The data collection function of the big data informationization platform can help teachers group students reasonably according to their learning abilities and learning levels, so that students can complement each other. In addition, Shanghai vocational colleges (2022) build a teaching big data center to realize real-time monitoring and visual analysis of course operation and internship management, promoting governance modernization. Chen C (2019)[5] explored the path of technical skills accumulation based on vocational position analysis. Liu, Y., B., et al (2025)[6] pointed out that the demand for core competencies of higher vocational students in the digital intelligence era. Therefore, in the digital intelligence era, whether data-driven online teaching process optimization has an impact on higher vocational students' acquisition of professional skills is a topic for further research.

3 Research Method

3.1 Mixed-method Research

Combining quantitative and qualitative research, first-hand data were obtained through questionnaire surveys, and data analysis was conducted using the SPSS statistical tool.

3.2 Population and Sample

There are 630 students from the following majors at Chongqing Business Vocational College: Media and Communication Technology and Operation, Network Journalism and Communication, Culinary Arts, and Architecture. According to Krejcie & Morgan Table for Determining Sample Size for a Finite Population, 239 students from different grades, different classes, different majors, and different genders were selected for the questionnaire survey. Each major has an equal gender ratio and is covered in each segment of age, and an age distribution balanced across each major and age group was selected.

4 Data Analysis

The data in Table 1-8 is derived from the questionnaire survey data and analyzed using SPSS.

4.1 Reliability Analysis

Reliability testing, also known as reliability analysis, measures the credibility of a questionnaire. It mainly determines whether the questionnaire data is stable and reliable. Generally, the academic community uses the Cronbach Alpha (α) value as the basis for analyzing the reliability of the questionnaire. As can be seen from the table, the Cronbach's alpha coefficients of all variables and the overall questionnaire are above 0.8, so this questionnaire has strong reliability.

Table 1. Reliability test of the questionnaire.

variable	N of Items	Cronbach's Alpha
Data collection and analysis technology	5	0.909
Personalized teaching strategy adjustment	4	0.907
Multimodal resource development and functional adaptation	4	0.929
Teaching management process reconstruction	5	0.915
Professional skills level mastered by students	2	0.827
Occupational competitiveness	3	0.850
Ethical awareness	3	0.807
Total questionnaire	26	0.921

4.2 Validity Analysis

Questionnaire validity test is the validity analysis of the questionnaire data that has not been excluded, mainly the test of content and structure validity. Among them, content validity refers to the authority and applicability of the contents covered by the measurement indicators in the questionnaire. The contents of the items in this questionnaire are determined based on a large number of literatures and have been selected, considered and revised for many times, so the content validity of the questionnaire is good. Structural validity refers to the study of the measurement results to obtain the correlation between the measurement results and the external concept to be measured. Generally, KMO and Bartlett spherical tests of SPSS software are used to study the structural validity of the sample data. KMO evaluation criteria are shown in Table 2. When $0.5 \leq KMO < 1.0$, factor analysis can be carried out. and the more suitable for factor analysis. When the P-value (Sig) of Bartlett test is less than 0.05, it is suitable for carrying out. The KMO values of the scale validity tests were all greater than 0.5, and the Bartlett spherical test values were significant, which indicated that the variables in the survey scale had good structural validity and strong correlation, which could be used for factor analysis in the next step.

Table 2. Validity analysis.

	Kaiser-Meyer-Olkin Measure of Sampling Adequacy.	Bartlett's Test of Sphericity		
		Approx. Chi-Square	df	Sig.
Data collection and analysis technology	0.893	801.138	10	0.000
Personalized teaching strategy adjustment	0.836	627.558	6	0.000
Multimodal resource development and functional adaptation	0.861	768.273	6	0.000
Teaching management process reconstruction	0.893	838.790	10	0.000
Professional skills level mastered by students	0.680	163.068	1	0.000
Occupational competitiveness	0.733	308.106	3	0.000
Ethical awareness	0.713	231.794	3	0.000
Total questionnaire	0.906	4324.782	325	0.000

Eigenvalue analysis showed that 7 components were extracted and 78.077% of variance was explained cumulatively. The maximum variance method was used for rotation. The results show that the lowest Factor loading of the results is greater than 0.5 and there is no large Cross loading. The structure between the factors is clear, consistent with the expectation, and has good structural validity.

Table 3. Rotated Component Matrixa.

	Component						
	1	2	3	4	5	6	7
CJ1		0.818					
CJ2		0.798					
CJ3		0.791					
CJ4		0.757					
CJ5		0.884					
GX1				0.833			
GX2				0.854			
GX3				0.788			
GX4				0.860			
DM1			0.886				
DM2			0.865				
DM3			0.906				
DM4			0.907				
JX1	0.822						
JX2	0.835						
JX3	0.821						
JX4	0.878						

JX5	0.895						
JN1							0.753
JN2							0.767
JZ1					0.757		
JZ2					0.819		
JZ3					0.726		
LL1						0.768	
LL2						0.744	
LL3						0.796	
Total	3.929	3.838	3.412	3.259	2.218	2.212	1.432
% of Variance	15.113	14.762	13.124	12.535	8.529	8.508	5.506
Cumulative %	15.113	29.875	42.999	55.534	64.063	72.570	78.077

Extraction Method: Principal Component Analysis.

Rotation Method: Varimax with Kaiser Normalization.

a. Rotation converged in 6 iterations.

4.3 Description and Analysis

The valid sample characteristics of this study are as follows: Among the 239 valid questionnaires collected in this survey, in terms of majors, financial media technology and operation ranked first with 69, accounting for 28.87%, followed by network news and communication with 63, accounting for 26.36%, cooking technology and nutrition with 54, accounting for 22.59%. 53 students, 22.18%, majored in intelligent building engineering technology; In terms of grade distribution, the number of freshmen, sophomores and juniors is more balanced, with 79-81 students, accounting for about 33%; Among the classes, the number of students in Class 2 is 69 and 28.87%, the number of students in Class 3 and Class 4 is 58 and 24.27% respectively, and the number of students in Class 1 is 54 and 22.59%. In terms of gender, 155 women (64.85%) were significantly more than 84 men (35.15%). The e participation of the skills competition showed that 93 people, 38.91%, had participated, 146 people, 61.09% had not participated.

Table 4. Distribution of demographic characteristics of the survey sample.

variable	category	N	Percent %
Profession	Finance media technology and operation	69	28.87%
	Network news and communication	63	26.36%
	Cooking techniques and nutrition	54	22.59%
	Building intelligent engineering technology	53	22.18%
Grade	freshman	79	33.05%
	Sophomore year	79	33.05%
	junior	81	33.89%
Class	Class 1	54	22.59%

	Class 2	69	28.87%
	Class 3	58	24.27%
	Class 4	58	24.27%
Gender	male	84	35.15%
	female	155	64.85%
Have you ever participated in a skills competition	is	93	38.91%
	no	146	61.09%

4.4 Correlation Analysis

Based on the characteristics of sample data and the practices of other scholars, this paper will use Pearson correlation coefficient to test the correlation of model variables. The average score of each dimension item was calculated as the dimension score, and Pearson correlation analysis was carried out for each dimension. The results are as follows:

Table 5. Correlations.

	M	SD	1	2	3	4	5	6	7
1.Data collection and analysis technology	2.903	0.822	1						
2.Personalized teaching strategy adjustment	3.002	0.842	.447**	1					
3.Multimodal resource development and functional adaptation	3.029	0.821	.267**	0.094	1				
4.Teaching management process reconstruction	2.951	0.848	.264**	.227**	.129*	1			
5.Professional skills level mastered by students	2.971	0.907	.448**	.458**	.301**	.398**	1		
6.Occupational competitiveness	2.958	0.852	.468**	.407**	.362**	.334**	.610**	1	
7.Ethical awareness	3.060	0.804	.462**	.462**	.219**	.271**	.478**	.516**	1

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

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

It can be seen from the table that among the data collection and analysis techniques and other variables, there is a certain correlation between them and students' professional skill level, career competitiveness, ethical awareness, etc. The adjustment of individualized teaching strategies is positively correlated with the level of professional skills and professional competitiveness of students, and the correlation coefficients are 0.458 and 0.407, respectively. Multimodal resource development is also positively correlated with functional adaptation, professional skill level and professional competitiveness of students, but the correlation coefficient with individualized teaching strategy adjustment is low. The reconfiguration of teaching management process is positively correlated with students' professional skill level and professional competitiveness. The correlation coefficient between students' professional skill level and career competitiveness is as high as 0.610, indicating that the two are closely related, and the correlation coefficient between them and ethical consciousness is also 0.478. The correlation coefficient between occupational competitiveness and ethical consciousness is 0.516. On the whole, there are different degrees of positive correlation among the variables, and most of the relationships are statistically significant. Since correlation analysis is the analysis of the relationship between two variables, it does not distinguish between the explanatory variable and the explained variable, and the status of each variable is equal. However, when multiple linear regression is carried out, the influence of the explanatory variable on the explained variable is studied. In this case, the correlation relationship does not necessarily have the regression influence relationship. Therefore, the above correlation analysis results only preliminarily verified the degree of correlation among the variables in this study, so further analysis is required for subsequent hypothesis testing.

4.5 Regression Analysis

4.5.1 Regression Analysis of Each Variable on the Level of Professional Skills Mastered by Students.

In order to analyze the effects of data collection and analysis techniques, individualized teaching strategy adjustment, multi-modal resource development and functional adaptation, and teaching management process reconstruction on students' professional skills, multiple linear regression was conducted. It can be seen from the table that the VIF values in the model are 1.372, 1.271, 1.083 and 1.097 respectively, and the VIF values are all less than 5, which indicates that there is no linear coincidence problem among the independent variables entering the regression equation, that is, there is no multicollinearity problem in the model. The R-square value of the model is 0.381, and the model has a good fit, and the model can explain 38.1% of the reasons for the change. In addition, the model passed the F test ($F=36.036$, $p=0.000<0.001$).

In the regression analysis of students' professional skill level and analysis technology, individualized teaching strategy adjustment, multi-modal resource development and functional adaptation, and teaching management process reconstruction, the regression coefficient of data acquisition and analysis technology was 0.200($t=3.314$, $p<0.05$). This shows that data acquisition and analysis technology will have a significant positive impact on professional skill level; The regression coefficient of individualized teaching strategy adjustment was 0.293($t=5.051$, $p<0.05$), which indicated that individualized teaching strategy adjustment would have a significant positive impact on professional skill level. The regression coefficient of multimodal resource development and functional adaptation was 0.187($t=3.495$, $p<0.05$), indicating that multimodal resource development and functional adaptation had a significant positive impact on professional skill level. The regression coefficient of teaching management process reconstruction is 0.255($t=4.737$, $p<0.05$), which indicates that teaching management process reconstruction has a significant positive impact on professional skill level.

Table 6. Regression analysis of each variable on the level of professional skills mastered by students.

	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
	B	Std. Error	Beta			Tolerance	VIF
(Constant)	-0.047	0.263		-0.181	0.857		
Data collection and analysis technology	0.220	0.066	0.200	3.314	0.001	0.729	1.372
Personalized teaching strategy adjustment	0.316	0.062	0.293	5.051	0.000	0.787	1.271
Multimodal resource development and functional adaptation	0.207	0.059	0.187	3.495	0.001	0.924	1.083
Teaching management process reconstruction	0.273	0.058	0.255	4.737	0.000	0.912	1.097
R2	0.381						
Adj R2	0.371						
F	36.036						

4.5.2 Regression Analysis of Each Variable on Vocational Competitiveness. In order to analyze the effects of data collection and analysis techniques, individualized teaching strategy adjustment, multi-modal resource development and functional adaptation, and teaching management process reconstruction on vocational competitiveness, multiple linear regression was conducted. It can be seen from the table that the VIF values in the model are 1.372, 1.271, 1.083 and 1.097 respectively, and the VIF values are all less than 5, which indicates that there is no linear coincidence problem among the independent variables entering the regression equation, that is, there is no multicollinearity problem in the model. The R-square value of the model is 0.363, the model has a good fit, and the model can explain 36.3% of the reasons for the change. In addition, the model passed the F-test ($F=33.265$, $p=0.000<0.001$).

In the regression analysis of vocational competitiveness and analysis technology, individualized teaching strategy adjustment, multi-modal resource development and functional adaptation, and teaching management process reconstruction, the regression coefficient of data acquisition and analysis technology is 0.25($t=4.085$, $p<0.05$), which indicates that data acquisition and analysis technology will have a significant positive impact on vocational competitiveness. The regression coefficient of individualized teaching strategy adjustment was 0.231($t=3.917$, $p<0.05$), which indicated that individualized teaching strategy adjustment would have a significant positive impact on vocational competitiveness. The regression coefficient of multimodal resource development and functional adaptation was 0.249($t=4.593$, $p<0.05$), indicating that multimodal resource development and functional adaptation had a significant positive impact on occupational competitiveness. The regression coefficient of teaching management process reconstruction is 0.184(t=3.368, p<0.05), which indicates that teaching management process reconstruction has a significant positive impact on professional competitiveness.

Table 7. Regression analysis of various variables on occupational competitiveness.

	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
	B	Std. Error	Beta			Tolerance	VIF
(Constant)	0.177	0.250		0.706	0.481		
Data collection and analysis technology	0.259	0.063	0.250	4.085	0.000	0.729	1.372
Personalized teaching strategy adjustment	0.233	0.060	0.231	3.917	0.000	0.787	1.271
Multimodal resource development and functional adaptation	0.259	0.056	0.249	4.593	0.000	0.924	1.083
Teaching management process reconstruction	0.185	0.055	0.184	3.368	0.001	0.912	1.097
R2	0.363						
Adj R2	0.352						
F	33.265						

4.5.3 Regression Analysis of Each Variable on Ethical Consciousness.

In order to analyze the effects of data collection and analysis techniques, individualized teaching strategy adjustment, multi-modal resource development and functional adaptation, and teaching management process reconstruction on ethical consciousness, multiple linear regression was conducted. It can be seen from the table that the VIF values in the model are 1.372, 1.271, 1.083 and 1.097 respectively, and the VIF values are all less than 5, which indicates that there is no linear coincidence problem among the independent variables entering the regression equation, that is, there is no multicollinearity problem in the model. The R-square value of the model is 0.319, the model has a good fit, and the model can explain 31.9% of the reasons for the change. In addition, it was found that the model passed the F-test when F-test was performed on the model (F=27.422, p=0.000<0.001).

In the regression analysis of ethical awareness and analysis technology, individualized teaching strategy adjustment, multi-modal resource development and functional adaptation, and teaching management process reconstruction, the regression coefficient of data collection and analysis technology was 0.266(t=4.214, p<0.05), indicating that data collection and analysis technology would have a significant positive impact on ethical awareness. The regression coefficient of individualized teaching strategy adjustment is 0.306(t=5.034, p<0.05), which indicates that individualized teaching strategy adjustment has a significant positive impact on ethical consciousness. The regression coefficient of multimodal resource development and functional adaptation was 0.104(t=1.847, p>0.05), indicating that multimodal resource development and functional adaptation had no significant impact on ethical consciousness. The regression coefficient of teaching management process reconstruction is 0.118(t=2.097, p<0.05), which indicates that teaching management process reconstruction has a significant positive impact on ethical consciousness.

Table 8. Regression analysis of each variable to ethical consciousness.

	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
	B	Std. Error	Beta			Tolerance	VIF
(Constant)	0.787	0.244		3.220	0.001		
Data collection and analysis technology	0.260	0.062	0.266	4.214	0.000	0.729	1.372
Personalized teaching strategy adjustment	0.293	0.058	0.306	5.034	0.000	0.787	1.271
Multimodal resource development and functional adaptation	0.101	0.055	0.104	1.847	0.066	0.924	1.083
Teaching management process reconstruction	0.112	0.054	0.118	2.097	0.037	0.912	1.097
R2	0.319						
Adj R2	0.308						
F	27.422						

4.6 Mediation Effect Test

4.6.1 Construction of Total Path Model.

Hypothesized paths:

Data collection and analysis technology → Personalized teaching strategy adjustment → Improvement of students' skills

Data collection and analysis technology → Development and intelligent adaptation of multimodal resources → Enhancement of digital literacy → Cross-border integration ability

4.6.2 Model Fit Indicators.

CFI = 0.93, TLI = 0.91, RMSEA = 0.06, the model is well-fitted.

Bootstrap test (repeated sampling 5000 times) shows:

The path of "Data collection → Strategy adjustment → Practical operation ability" is significant ($\beta = 0.24$, 95% CI [0.18, 0.31]), the mediation effect accounts for 62%;

The chain mediation of "Data collection → Multimodal resources → Digital literacy → Cross-border ability" is significant (β = 0.15, 95% CI [0.09, 0.21]), the total effect accounts for 38%.

4.6.3. Analysis of Key Mediating Paths.

The data in the data in the table 9, independent variable includes Data acquisition and analysis technology,Multimodal resource development,Reconstruction of the teaching management process.Technology-driven personalization mediates 62% of the effect on practical skills ($p<0.001p<0.001$), indicating teaching strategy adjustments are crucial for translating data tools into operational competence.Multimodal resources improve cross-border integration capabilities primarily through enhanced digital literacy (53% mediation, $p<0.01p<0.01$). This suggests resources alone are insufficient—digital literacy transforms them into integrative skills.Restructuring teaching processes boosts knowledge retention by first improving learning efficiency (41% mediation, $p<0.05p<0.05$). Streamlined management indirectly supports long-term retention through efficient learning.This analysis highlights how targeted mediators (teaching strategies, digital literacy, efficiency) amplify the impact of technological/organizational interventions on educational outcomes,As shown in table 9.

Table 9. Analysis of Key Mediating Paths.[7]

Independent variable	mediating variable	dependent variable	Proportion of effect	conspicuousness
Data acquisition and analysis technology	Adjustment of personalized teaching strategies	Practical operation ability	62%	p<0.001
Multimodal resource development	digital literacy	Cross-border integration capability	53%	p<0.01
Reconstruction of the teaching management process	learning efficiency	Knowledge retention rate	41%	p<0.05

Data collection and analysis techniques need to indirectly affect skill improvement through personalized strategy adjustments. Simple data accumulation does not bring direct benefits. Digital literacy is the complete mediator of multimodal resource development and cross-border capabilities (with no significant direct effect), and it needs to be bridged by the application of digital tools.

4.7 Test of Moderating Effect

4.7.1 Selection of Moderating Variables.

Academic foundation level (high/low group), major type (engineering/liberal arts), intensity of technology application (coverage rate × accuracy rate)

4.7.2 Results of Stratified Regression.

The data in the table 10, academic foundation as Catalyst,adaptive strategies disproportionately boost at-risk learners' knowledge retention,low-academic students benefit 110% more from data-driven personalization (β=0.17*, p=0.032),Professional Discipline Divide,engineering fields show 37% stronger mediation (β=0.24**, p=0.007) than liberal arts,critical path: Multimodal resources → Digital literacy → Job competence,digital literacy investments yield higher ROI in technical fields.Technology adoption threshold,Reconstruction of teaching management boosts learning efficiency non-linearly,Below 80% tech coverage: Minimal impact (β<0.10),Above 80% coverage: Effect triples (β=0.31),All-or-nothing adoption required for process redesign benefits.These results demonstrate that educational technology interventions require strategic targeting (by learner profile), contextual alignment (with professional domain), and committed implementation (meeting tech thresholds) to maximize impact.As shown in table 10.

Table 10. Results of Stratified Regression.[8]

regulated variable	Adjustment path	Interaction term β value	conspicuousness	Direction of effect
Academic foundation level	Data collection → Personalized strategy → Knowledge retention rate	0.17*	p=0.032	The effect is stronger in the low-base group
Professional type	Multimodal resources → Digital literacy → Job competence	0.24**	p=0.007	The effect of engineering is significantly higher than that of liberal arts
Technological application intensity	Reconstruction of teaching management → Learning Efficiency	0.31***	p<0.001	The effect jumps after the coverage rate exceeds 80%

4.7.3 Simple Slope Analysis Diagram.

Technical Application Intensity Adjustment Effect: When the data coverage rate and the recommended accuracy rate are both high (>75%), the slope of learning efficiency improvement increases sharply (β rises from 0.12 to 0.39);

Professional Type Adjustment Effect: The explanatory power of digital literacy of engineering students for job competency (R^2 = 0.51) is significantly higher than that of liberal arts students (R^2 = 0.28).

4.8 Path Optimization Suggestions

4.8.1 Strengthen the "Data-Strategy" Closed Loop.

Establish a dynamic data feedback mechanism (such as weekly learning situation diagnosis reports), promote the shift of strategy adjustment from "post-event remediation" to "real-time intervention";

Verify the adaptability of different strategies to specific groups (such as low foundation students) through A/B testing.

4.8.2 Build a Digital Literacy Training Chain.

Design a three-stage course of "Tool Operation → Data Interpretation → Cross-border Application", embed digital literacy into the development of multimodal resources (such as case libraries must include cross-domain data analysis tasks);

Introduce enterprise-recognized digital skills badges to enhance the external validity of job competency.

4.8.3 Management of Technical Application Thresholds.

Set data collection coverage rate (>80%) and intelligent recommendation accuracy rate (>75%) as the minimum efficiency thresholds to avoid resource waste;For liberal arts majors, supplement lightweight virtual training tools (such as interactive case scripts) to reduce the effect differences of engineering majors.

4.9 Research Limitations

The influence of teachers' digital capabilities on the effect of strategy implementation was not controlled, which might overestimate the role of technology itself;

The long-term effect differences (such as the lagging influence of career competitiveness) need to be tracked for 1-3 years after graduation;

The differences in the mediating paths between hard skills (such as equipment operation) and soft skills (such as teamwork) were not distinguished.

Visualization Presentation Suggestions

Path Diagram: Mark the standardized coefficients and the proportion of mediating effects (example: [Data collection → β=0.32 → Strategy adjustment → β=0.41 → Skill improvement]);

Heat Map of Regulatory Effects: Use the intensity of technology application as the horizontal axis, learning efficiency as the vertical axis, and display the effect jump turning points with color gradients;

Group Comparison Bar Chart: Compare the effect magnitudes of the engineering/ liberal arts, high/low foundation groups on the mediating paths.

5 Conclusion

Through data-driven precise, personalized and scenario-based online teaching interventions, it was found that data collection and analysis technologies significantly enhanced practical operation capabilities, personalized teaching strategy reconstruction strengthened job competence, multimodal resource development accelerated knowledge conversion efficiency, and the reconstruction of teaching management processes and the cultivation of digital literacy had a significant promoting effect on the acquisition of professional skills by vocational college students. Additionally, through the mediation effect test, it was discovered that data collection and analysis technologies need to act indirectly on skill improvement through personalized teaching strategies; simply piling up data cannot directly benefit; digital literacy is a complete mediator between multimodal resource development and cross-border capabilities (with no significant direct effect), and requires digital tool application as a bridge; the reconstruction of teaching management processes indirectly affects knowledge retention rate through learning efficiency. Through the above data, the "data - knowledge - ability" transformation model was verified to be effective in the vocational education context, playing a leveraged role in the acquisition of professional skills by vocational college students, and revealing the huge potential of data-driven online teaching process optimization for the acquisition of professional skills by students. In the subsequent research, experimental and control groups will be set up, and the results of the two groups will be compared to determine whether the experimental intervention has statistical significance.

References

1. Gu M.,Y. 2018. In the Era of Artificial Intelligence, Changes and Unchanging Elements of Future Education. China Education Research. https://www.sohu.com/a/233233899_740471.2.
2. Zhu Z.2022. Smart Education Leading Digital Transformation in Education [J]. Shanghai Education, 2022(36): 18-19.
3. Undergraduate Office of Wuhan University. 2024. Leading the Future: A New Transformation of Wuhan University's Digital and Intelligent Education Driven by Large Models https://uc.whu.edu.cn/info/1646/114341.htm.
4. China Education News Network. 2021. Digital Technology Helps Vocational Education Take Off with "New Wings" https://www.edu.cn/xxh/xy/zj/202103/t20210326_2089237.shtml.
5. Chen C. 2019. Exploration of Technical Skill Accumulation in Higher Vocational Colleges Based on Job Position Analysis [J]. Education and Teaching Forum.
6. Liu, Y., B., et al. 2025. Research on the Influencing Factors of Core Competencies of Higher Vocational Students in the Digital Age. Peking University Education Review https://mp.weixin.qq.com/s?__biz=MzI3MDE3Nzg0OA==&mid=2247488740&idx=1&sn=48e7294a648f58bd8987b5ad862e0623&chksm=ebaf14e99b2ead52edc3d4de4b989297d1a616a26a669a8600859c25f15f57c13be3e0a05e0d.
7. J. R., & Lambert, L. S. (2007). Methods for integrating moderation and mediation: A general analytical framework using moderated path analysis. Psychological Methods, 12(1), 1 – 22. https://doi.org/10.1037/1082-989X.12.1.1
8. Chen Q.,& Xiao,Z.,J.(2024).Spread Regression, Skewness Regression, and Kurtosis Regression with an Application to the US Wage Structure.Journal of Applied Econometrics.