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Enhancing Academic Achievement in Computer Science Students: An Experimental Study on the Efficacy of Deep Learning Teaching Methods in Higher Vocational Education

Chen Jing[1], Charanjit Kaur Swaran Singh[2]

[1] Infrastructure University Kuala Lumpur, Kuala Lumpur, Malaysia
[2] Universiti Pendidikan Sultan Idris, Boulder, Kuala Lumpur, Malaysia

Abstract: In the era of digital transformation, the integration of information technology into learning has posed challenges and opportunities. Navigating the global knowledge economy requires individuals to acquire skills facilitating adaptation to evolving economic and societal landscapes. Deep learning, recognized as pivotal for addressing real-world challenges and fostering adaptive capabilities, has garnered attention in educational research. This study investigates the effect of a deep learning teaching approach on the academic achievement of computer science students at a higher vocational institution. Employing an experimental research method with an experimental and control group, the study involved pre- and post-tests for first-grade computer science students. Results from a quasi-experimental analysis at a vocational college reveal that the implementation of deep learning teaching methods significantly enhanced both deep learning levels and academic performance in the experimental group, surpassing the outcomes of the control group under traditional teaching methods. Statistical analyses, including paired samples t-tests and independent samples t-tests, underscore the ineffectiveness of traditional teaching in fostering deep learning levels. The study provides robust evidence supporting the practical and substantial benefits of integrating deep learning methods into educational practices, emphasizing their potential for enhancing student outcomes.

Keywords: Strategy; Deep Learning; Achievement; Vocational Education.

1. Introduction

In the digital landscape, the advent of information technology has presented both opportunities and challenges in the domain of learning. To succeed in the global knowledge economy, individuals must cultivate skills that enable them to adapt to new modes of economic and social development. This adaptation involves not only the creation and application of knowledge for human development but also necessitates advanced learning abilities to comprehend intricate concepts, construct individualized knowledge systems, and effectively address real-world problems. Scholars from diverse countries are actively investigating various teaching models and learning methods, with a focus on designing technology-supported learning environments to foster talents equipped with deep learning skills (Hava, 2021; Sabah et al., 2023; Jamil & Bhuiyan, 2021; LoGiudice et al., 2023; Li et al., 2022; Weng et al., 2023). This recognition of deep learning as a crucial variable, enabling individuals to adapt to environmental changes and provide practical solutions, underscores its significance. Additionally, achievement is the primary variable determining learners' transitions between stages and represents a key goal for educational institutions. Therefore, it is significant to establish an effective deep learning teaching environment aimed at improving students' deep learning abilities and elevating academic achievement.

2. The Theoretical Framework

2.1. Deep Learning

In the context of education, deep learning is primarily viewed as an effective learning approach (Sabah et al., 2023; Zhang et al., 2021) and process (Weng et al., 2023; Xie et al., 2023) aimed at promoting knowledge transfer and developing higher-order thinking skills (Weng et al., 2023; Xie et al., 2023). The objective is to enhance the quality of students' learning achievement (Hava, 2021; LoGiudice et al., 2023; Zhang et al., 2021).

Various researchers have provided distinct definitions of deep learning, depending on their focus on either the learning process or its resultant outcomes. When viewed as outcomes, deep learning is interpreted as a set of competencies (Advance HE, 2020; AIR, 2022; Jamil & Bhuiyan, 2021; Otto et al., 2020). When viewed as a variable within the learning process, "deep learning" is initially characterized as a knowledge transfer process that enables learners to enhance their problem-solving and decision-making abilities (Han et al., 2023; Hava, 2021; Li et al., 2022; Weng et al., 2023; Xie et al., 2023). Among these scholars, Biggs' work has been frequently referenced (Han et al., 2023; Hava, 2021; Li et al., 2022; Xie et al., 2023). He defined a deep learning approach as necessitating strategies such as critically understanding new concepts, linking novel ideas and concepts, and associating fresh knowledge with prior understanding (Hava, 2021).

In accordance with constructivist theory, constructive learning emerges through the construction of structured and unstructured knowledge meanings (Bada & Olusegun, 2015). Aligned with this perspective, deep learning is conceptualized as a cognitive process and its corresponding cognitive outcome, involving the reconstruction of both prior and additional knowledge. By integrating constructivist principles with both domestic and international perspectives on deep learning, the concept can be characterized as an advanced cognitive process wherein learners are guided towards specific learning outcomes. This process involves the establishment of clear learning objectives, comprehensive understanding, analysis, and resolution of complex problems, along with the critical synthesis, transfer, and innovation of knowledge.

2.2. Achievement

Achievement, in the educational domain, is frequently synonymous with academic achievement, reflecting not only the mastery of subject matter but also the application of acquired knowledge in real-world scenarios. The evaluation of educational methods and strategies heavily relies on measuring student achievement, a multidimensional construct encompassing academic achievement, knowledge acquisition, and the application of learned concepts. This comprehensive understanding of achievement aligns with the holistic goals of education, aspiring to develop individuals capable of critical thinking, problem-solving, and effective decision-making. The exploration of achievement as a dependent variable necessitates a thorough examination of its diverse dimensions, whether manifested through standardized test scores, project outcomes, or other measurable indicators. Achievement serves as a tangible metric to assess the efficacy of teaching interventions.

This study aims to explore and quantify the influence of deep learning instructional approaches on student achievement, seeking to discern patterns and correlations contributing to educational success. At the core of this investigation is the exploration of the dependent variable, "achievement," serving as a comprehensive measure of students' academic success and competence. This provides valuable insights into the effectiveness of diverse teaching methodologies. The study draws on a rich body of literature, with scholars such as Han et al. (2023), Hava (2021), Li et al. (2022), Weng et al. (2023), and Xie et al. (2023) contributing valuable insights into the conceptualization and measurement of deep learning, a factor intricately linked to achievement outcomes. This research delves into the nuanced dimensions of achievement as a dependent variable, aiming to unravel the intricate relationship between deep learning teaching approaches and student success.

2.3. Significance

Althought the abundance of research studies testing deep learning methods in higher education, applying the results without critical analysis poses a challenge. A recent empirical study highlights insufficient empirical evidence regarding the effects of deep learning implemented in learning environments (Otto et al., 2020). Additionally, criticisms have been directed at the predictive validity of these studies due to sparse empirical support and ambiguity regarding specific outcome measures indicating whether deep learning has occurred (LoGiudice et al., 2023). In this context, there is a pressing need for more effective empirical research in the field. Therefore, the study sought to investigate the research question: Does the deep learning teaching approach significantly impact students' achievement compared to the traditional method?

3. Methodology

The study employed a quasi-experimental design with quantitative methods (Creswell, 2018) to explore the impact of a deep learning teaching approach on the academic achievement of computer science students in a selected higher vocational education institution in China. This design treated the deep learning teaching approach as the independent variable and academic achievement as the dependent variable. Employing an experimental research method, the study included two experimental groups and a control group, each undergoing pre-test and post-test assessments.

3.1. Participants

The research population comprised all computer science students at Guangxi Vocational and Technical Institution of Industry (GTI). This population was chosen for several reasons. Firstly, the students were studying computer science; the artificial intelligence course they had chosen was optional, and therefore, they were likely to have a more positive attitude towards it and less perceived pressure and challenges. Secondly, participants were chosen from students who enrolled in the course through the on-campus learning platform, as it facilitated data collection about the learners' learning processes and since they were already familiar with the learning environment. Conclusively, these participants exhibited comparable levels of professional competence, thereby mitigating potential experimental errors.

The participants were full-time second-year students in four classes pursuing a Computer Science major at GTI. Due to instructional constraints preventing random assignment, purposive sampling was employed to select two classes, each consisting of 30 students, from the institution. While this non-random assignment may introduce threats to internal validity and potential bias, efforts were made to mitigate these issues through pre-testing. Before commencing the research, pre-test were conducted on the selected four classes, extracting the average scores from the previous semester's final exams as pretest data.

The subsequent step involved identifying two classes with the most closely matched score distributions among the four. In educational research, particularly in the comparison of student performance, Analysis of Variance (ANOVA) is a statistical method employed to determine differences between classes. The aim was to identify the two classes with the smallest score differences. This study utilized ANOVA and post hoc testing for class selection. Initially, ANOVA was employed to examine whether there were significant differences in the average scores among the multiple classes. If ANOVA indicated significant differences, post hoc testing (LSD test) was used to compare specific differences between the classes. The results are presented in Tables 1 and 2. The ANOVA results indicated a significant difference in pre-test scores among the four classes ($F(3, 113) = 5.871$, $p = 0.001$).

Table 1. ANOVA

	square sum (e.g. equation of squares)	df	mean square	F	significance
inter-cluster	615.720	3	205.240	5.871	.001
in-group	3950.246	113	34.958		
total	4565.966	116			

Table 2. Post hoc multiple comparisons

Dependent variable: pre-test scores						
LSD						
					Difference 95% confidence interval	
(I) class	(J) class	Mean difference (I-J)	standard error	significance	lower limit	limit
Class 1	Class 2	-2.76970	1.56651	.080	-5.8732	.3338
	Class 3	-5.94828*	1.53971	.000	-8.9987	-2.8978
	Class 4	-4.98161*	1.53971	.002	-8.0321	-1.9312
Class 2	Class 1	2.76970	1.56651	.080	-.3338	5.8732
	Class 3	-3.17857*	1.55363	.043	-6.2566	-.1006
	Class 4	-2.21190	1.55363	.157	-5.2899	.8661
Class 3	Class 1	5.94828*	1.53971	.000	2.8978	8.9987
	Class 2	3.17857*	1.55363	.043	.1006	6.2566
	Class 4	.96667	1.52661	.528	-2.0578	3.9912
Class 4	Class 1	4.98161*	1.53971	.002	1.9312	8.0321
	Class 2	2.21190	1.55363	.157	-.8661	5.2899
	Class 3	-.96667	1.52661	.528	-3.9912	2.0578

*. Differences in means are significant at the 0.05 level.

Post hoc multiple comparison results reveal that the pre-test score differences between Class 1 and Class 2 are not significant (M(I-J) = -2.770, p = 0.080), whereas the differences between Class 1 and Class 3 are significant (M(I-J) = -5.948, p = 0.000), as well as between Class 1 and Class 4 (M(I-J) = -4.982, p = 0.002). Additionally, the pre-test score differences between Class 2 and Class 3 are significant (M(I-J) = -3.179, p = 0.043), while those between Class 2 and Class 4 are not significant (M(I-J) = -2.212, p = 0.157), and Class 3 and Class 4 exhibit non-significant differences in pre-test scores (M(I-J) = 0.967, p = 0.528). Based on the average difference values and significance values across the groups, it is evident that the pre-test score distributions of Class 3 and Class 4 are the most closely matched.

Therefore, based on the results of the ANOVA and the post-test, the researcher chose the two classes with the closest scores, i.e., [Class 3] and [Class 4], for the follow-up experiment. Table 3 presents the comparison of [descriptive statistics] (mean, standard deviation, standard error, and number of participants) between the participants' pre-test and post-test.

Table 3. Comparison of Test Scores of the Two Groups

	Group	Mean	Std.Deviation	SE	N
Pre-test	control group	82.533	5.329	0.973	30
	Experimental group	83.500	5.463	0.997	30
	Total	83.017	5.373	0.694	60
Post-test	control group	78.767	8.282	1.512	30
	experimental group	86.333	7.884	1.439	30
	Total	82.550	8.879	1.146	60

3.2. Research Procedure

The primary objective of this research was to assess whether participants who underwent deep learning teaching methods (experimental group) exhibited significantly superior performance compared to a similar group (control group) not subjected to the same intervention. The research adopted a robust experimental design involving class selection, random group assignment, course content design, time framework, data collection, exams, evaluation, data analysis, and result interpretation. The research steps are outlined in table 4.

In the research design, two comparable classes, namely Computer class 3 and Computer class 4, were selected to ensure similarity in student backgrounds, prior knowledge levels, and other relevant aspects. The random division of the two classes into experimental and control groups was implemented. The experimental group (Computer class 3) underwent deep learning teaching methods, while the control group (Computer class 4) experienced traditional teaching methods. Consistent course content was developed to ensure that students in both groups encountered similar knowledge and skills. Content consistency was maintained between deep learning and traditional teaching methods in the "Artificial Intelligence Techniques" Practical Training Course.

To further standardize the experiment, an equal amount of teaching and practice time was allocated to both the experimental and control groups during the Fall/Winter semester of 2023. Baseline data, including students' previous academic achievement and background information, was collected. Throughout the experiment, classroom participation and assignment completion were recorded. Average student scores at the end of the previous semester for both classes and pre-test scores from the Deep Learning Competency Test questionnaire were used as baseline measures.

Identical exams and evaluations were administered to assess students' academic achievement under both deep learning and traditional teaching methods. To ensure uniform difficulty and content across both groups, final exam scores for the course and post-test scores from the Deep Learning Competency Test questionnaire were collected. Statistical analysis methods, such as t-tests or analysis of variance, were employed to compare the grades of students in both groups, considering potential confounding factors like individual student differences.

The collected data were analyzed using SPSS software based on hypothese. The results of data analysis were then interpreted to understand the effects of deep learning and traditional teaching methods on student performance. In the discussion section, the limitations of the experiment were addressed, and suggestions for future improvements and further research were proposed based on the obtained results.

Table 4. Research Steps

step	description	result
Class Selection	Choose two comparable classes, ensuring similarity in student backgrounds, prior knowledge levels, and other relevant aspects.	Computer class 3, Computer class 4
Random Group Assignment	Randomly divide the two classes into experimental and control groups. The experimental group will experience deep learning teaching methods, while the control group will undergo traditional teaching methods.	Experimental group: Computer class 3, control group-Computer class 4
Course Content Design	Develop consistent course content, ensuring students in both groups encounter similar knowledge and skills. Maintain content consistency between deep learning and traditional teaching methods.	Course: "Artificial Intelligence Techniques" Practical Training Course
Time Framework	Determine the time framework for the experiment, such as one semester. Allocate an equal amount of teaching and practice time in both the experimental and control groups.	Fall/Winter semester 2023
Data Collection	Collect baseline data, including students' previous academic achievement and background information. Throughout the experiment, record classroom participation and assignment completion.	Average student scores at the end of the previous semester for both classes, Deep Learning Competency Test questionnaire pre-test scores.
Exams and Evaluation	Administer identical exams and evaluations to assess students' academic achievement under deep learning and traditional teaching methods. Ensure uniform difficulty and content across both groups.	Final exam scores for the course, Deep Learning Competency Test questionnaire post-test scores
Data Analysis	Utilize statistical analysis methods, such as t-tests or analysis of variance, to compare the grades of students in both groups. Consider controlling for potential confounding factors like individual student differences.	Data were analyzed using SPSS software based on hypothese
Result Interpretation	Based on the results of data analysis, interpret the effects of deep learning and traditional teaching methods on student performance. Discuss the limitations of the experiment and propose suggestions for future improvements and further research.	Discussion of the results

4. Results

4.1. Research Question 1: What are the Effects between the Deep Learning Teaching Approach and the Traditional Teaching Approach on Students' Achievement in the Course Registered in Terms of Pre-test Scores?

To verify whether there is no significant difference in the levels of deep learning and academic achievement between the experimental and control groups before the start of the experiment, this study employs a t-test to analyze the collected data.

4.1.1. Pre-test Analysis of Variability in the Level of Deep Learning

To verify whether there is a significant difference in the levels of deep learning between the experimental and control groups before the start of the experiment, this study proposes the null hypothesis (H01): There is no significant difference in the pre-test using R-SPQ-2F between the experimental group and the control group. The independent samples t-test results are shown in Table 5 and 6.

Independent samples t-tests were conducted on the pre-test data of deep learning proficiency for students in the experimental and control groups. The descriptive statistics results are presented in Table 5. The average deep learning proficiency score for the experimental group students is 65.4333, while for the control group students, it is 64.0000. The results of the statistical analysis (see Table 6) indicate that the p-value (sig.) is 0.098, which is greater than the significance level of 0.05. Upon analysis, it is evident that there is no significant difference in the deep learning proficiency between students in the experimental and control groups. The deep learning proficiency levels of students in both groups are similar.

Table 5. Descriptive Statistics

item	Class classification	N	mean value	Standard deviation	Standard error mean
R-SPQ-2F	control group	30	64.0000	3.32182	.60648
	experimental group	30	65.4333	3.28721	.60016

Table 6. Independent Sample Tests

item		Levene's Test for Homogeneity of Variances		Mean equivalence t-test					Difference 95% confidence interval	
		F	significance	T	df	Sig.	Average difference	Standard error	Lower limit	limit
R-SPQ-2F	Assuming equal variance	.000	.993	-1.680	58	.098	-1.43333	.85323	-3.14127	.27460
	Not assuming equal variance			-1.680	57.994	.098	-1.43333	.85323	-3.14127	.27460

4.1.2. Pre-tst Analysis of Variability in Academic Achievement

In the selection of the experimental class, the end-of-semester grades from the previous semester were chosen as pre-test scores. This study utilized the end-of-semester grades from the preceding semester as pre-test scores and employed an independent samples t-test to determine whether there were significant differences in academic achievement between the two classes. The descriptive statistics results obtained from the analysis are presented in Table 7. The average academic achievement score for the experimental group students is 83.5000, while for the control group students, it is 82.5333. The results of the statistical analysis (see Table 8) indicate that the p-value (sig.) is 0.491, which is greater than the significance level of 0.05. Upon analysis, it is evident that there is no significant difference in academic achievement between students in the experimental and control groups. The academic achievement levels of students in both groups are similar.

Table 7. Descriptive Statistics

item	Class classification	N	mean value	standard deviation	Standard error mean
Pre-Test	control group	30	82.5333	5.32873	.97289
	experimental group	30	83.5000	5.46304	.99741

Table 8. Independent Sample Tests

item		Levene's Test for Homogeneity of Variances		Mean equivalence t-test					Difference 95% confidence interval	
		F	significance	T	df	Sig.	Average difference	Standard error	Lower limit	limit
Pre-Test	Assuming equal variance	.008	.931	-.694	58	.491	-.9667	1.3933	-3.7557	1.82237
	Not assuming equal variance			-.694	57.964	.491	-.9667	1.3933	-3.7557	1.82240

4.2. Research Question 2: What are the Effects of the Traditional Teaching Approach on Students' Performance in the Course Registered in Terms of the Pre-test and Post-test Scores?

The second research question considers using the paired sample t-test method. The null hypothesis (H02) for this study is: Students using traditional teaching methods (control group) have equal mean scores in pre-test and post-test assessments. This study utilizes the paired sample t-test to analyze the score data at the two time points, pre-test, and post-test.

4.2.1. Pre-test and Post-test Analysis of Variability in the Level of Deep Learning

To determine whether there is an improvement in the deep learning levels of students in the control group after a semester of learning without feedback intervention, and whether there are significant differences, this study will analyze the questionnaire data on the deep learning levels of control group students at two stages: before and after the experiment. Detailed analysis results are presented in Table 9 and Table 10.

Table 9. Statistics of matched samples

		mean value	N	Sd.	Standard error mean
Paired 1	pre-test	64.0000	30	3.32182	.60648
	Post-test	64.5333	30	4.20782	.76824

Table 10. Paired Samples Test

		(Math.) pairing difference					T	df	Significance (two- tailed)
		mean value	standard deviation	Standard Error mean	Difference 95% confidence interval				
					Lower limit	limit			
Paired 1	pre-test Post-test	-.53333	3.04827	.55654	-1.67158	.60491	-.958	29	.346

The results in Table 9 indicated that the average level of deep learning for control group students before the experiment is 64.0000, and after the experiment, it is 64.5333, with a p-value (significance) of 0.346, which is greater than 0.05 (refer to Table 10). The analysis reveals that there is no significant difference in the deep learning levels of control group students after a semester of learning without feedback intervention. In other words, there is no significant improvement in the level of deep learning of the students.

4.2.2. Pre-test and Post-test Analysis of Variability in Achievement

This study examined the academic achievement of the control group students before and after the experiment in two stages to ascertain whether the students' performance improved academically after a semester of learning without feedback intervention and whether there were any significant differences.

Table 11. Statistics of matched samples

		mean value	N	Sd.	Standard error mean
Paired 1	pre-test	82.5333	30	5.32873	.97289
	Post-test	78.7667	30	8.28244	1.51216

Table 12. Paired Samples Test

		(math.) pairing difference					T	df	Significance (two- tailed)
		mean value	standard deviation	Standard Error mean	Difference 95% confidence interval				
					Lower limit	limit			
Paired 1	pre-test Post-test	3.76667	5.76364	1.05229	1.61449	5.91885	3.579	29	.001

The results in Table 11 and 12 showed that the average academic achievement of the control group students before the experiment was 82.5333, and after the experiment, it was 78.7667, with P (sig.) = 0.001 < 0.05. Through analysis, it is evident that the academic achievement of the control group students significantly decreased after a semester of learning without feedback intervention.

4.3. Research Question 3: What are the Effects of the Deep Learning Teaching Approach on Students' Performance in the Course Registered in Terms of the Pre-test and Post-test Scores?

The third research question considers using the paired sample t-test method. The null hypothesis (H03) for this study is: the average scores of students using deep learning teaching methods (experimental group) are equal in the pre-test and post-test. This study utilizes the paired sample t-test to analyze the score data at the two time points, pre-test, and post-test.

4.3.1. Pre-test and Post-test Analysis of Variability in the Level of Deep Learning

To understand whether the deep learning proficiency of the experimental group students improved after the conclusion of the educational experiment, an analysis was conducted on the questionnaire data regarding the deep learning levels of the experimental group students before and after the experiment.

Table 13. Statistics of matched samples

		mean value	N	Sd.	Standard error mean
Paired 1	pre-test	65.4333	30	3.28721	.60016
	Post-test	88.4333	30	12.26906	2.24001

Table 14. Paired Samples Test

		(math.) pairing difference					T	df	Significance (two- tailed)
		mean value	standard deviation	Standard Error mean	Difference 95% confidence interval				
					Lower limit	limit			
Paired 1	pre-test Post-test	-23.0000	12.24463	2.23555	-27.57222	-18.42778	-10.288	29	.000

The results in Table 13 and 14 indicated that the average level of deep learning proficiency for the experimental group students was 65.4333 before the experiment and 88.4333 after the experiment, with P (sig.) = 0.000 < 0.05. Through analysis, it is evident that there is a significant difference in deep learning proficiency for the experimental group students between the pre-experiment and post-experiment stages, with the post-experiment level notably higher than the pre-experiment level.

4.3.2. Pre-test and Post-test Analysis of Variability in Achievement

To investigate whether the academic achievement of the experimental group students improves after a semester of learning with feedback intervention and whether there are significant differences, the academic achievement of the experimental group students before and after the experiment will be analyzed in two stages.

Table 15. Statistics of matched samples

		mean value	N	Sd.	Standard error mean
Paired 1	pre-test	83.5000	30	5.46304	.99741
	Post-test	86.3333	30	7.88422	1.43945

Table 16. Paired Samples Test

		(math.) pairing difference					T	df	Significance (two- tailed)
		mean value	standard deviation	Standard Error mean	Difference 95% confidence interval				
					Lower limit	limit			
Paired 1	pre-test Post-test	-2.83333	5.83144	1.06467	-5.01083	-.65584	-2.661	29	.013

The results in Table 15 and 16 indicated that the average score of experimental class students before the experiment was 83.5000, and after the experiment, it was 86.3333, with P (sig.) = 0.013 <0.05. Through analysis, it can be observed that the academic achievement of experimental group significantly improved after a semester of learning with feedback intervention.

4.4. Research Question 4: What are the Effects between the Deep Learning Teaching Approach and the Traditional Teaching Approach on Students' Achievement in the Course Registered in Terms of Post-Test Scores?

To study the difference in deep learning levels between students in the two classes after experiment, data analysis was conducted for both classes. The null hypothesis (H04): There is no significant difference between the experimental group and the control group.

4.4.1. Post-Test Analysis of Variability in the Level of Deep Learning

To understand the difference in deep learning levels between students in the two classes after the conclusion of the educational experiment, data analysis was conducted on the deep learning level questionnaire results for both classes. The null hypothesis (H04): There is no significant difference in the post-test questionnaire scores between the experimental group and the control group.

Table 17. Descriptive Statistics

item	Class classification	N	mean value	standard deviation	Standard error mean
questionnaire	control group	30	64.5333	4.20782	.76824
	experimental group	30	88.4333	12.26906	2.24001

Table 18. Independent Sample Tests

		Levene's Test for Homogeneity of Variances		Mean equivalence t-test						
									Difference 95% confidence interval	
item		F	significance	T	df	Sig.	Average difference	Standard error	Lower limit	limit
questionnaire	Assuming equal variance	54.552	.000	-10.093	58	.000	-23.90000	2.36809	-28.64025	-19.15975
	Not assuming equal variance			-10.093	35.729	.000	-23.90000	2.36809	-28.70398	-19.09602

The results in Table 17 and 18 indicated that the average deep learning level of the experimental group students was 88.4333, while the control group students had an average of 64.5333, with P (sig.) = 0.000 < 0.05. Through analysis, it was evident that after the implementation of the experiment, there was a significant difference in the deep learning levels between the students in the experimental and control groups, with the experimental group exhibiting a higher level of deep learning compared to the control group.

4.4.2. Post-Test Analysis of Variability in Academic Achievement

After the completion of the experiment, a comprehensive final project test was conducted, and independent sample t-tests were performed on the exam score data of the two classes, yielding results (refer to Table 19). The average final score for the experimental group students was 86.3333, while the control group students had an average score of 78.7667, with P (sig.) $= 0.001 < 0.05$ (refer to Table 20). Through analysis, it was evident that there was a significant difference in the final exam scores between the students in the experimental and control groups, with the experimental group students achieving significantly higher scores than the control group students.

Table 19. Descriptive Statistics

item	Class classification	N	mean value	standard deviation	Standard error mean
achievement	control group	30	78.7667	8.28244	1.51216
	experimental group	30	86.3333	7.88422	1.43945

Table 20. Independent Sample Tests

		Levene's Test for Homogeneity of Variances		Mean equivalence t-test						
									Difference 95% confidence interval	
item		F	significance	T	df	Sig.	Average difference	Standard error	Lower limit	limit
achievement	Assuming equal variance	.022	.883	-3.624	58	.001	-7.56667	2.0877	-11.74573	-3.38760
	Not assuming equal variance			-3.624	57.860	.001	-7.56667	2.0877	-11.74595	-3.38738

4.5. Research Question 5: What is the Effect Size of the Practical Significance (If Any) Between Deep Learning and Traditional Teaching Approaches in the Post-Test Scores?

To investigate whether there is a practical significance in the effect size of deep learning teaching methods compared to traditional teaching methods on post-test scores, an independent samples t-test can be employed to compare the mean post-test scores of the two teaching methods. The null hypothesis (H05) for this study is: There is no significant difference in post-test scores between deep learning teaching methods and traditional teaching methods. Use the independent samples t-test to compare the post-test scores of the two groups, calculating the t-statistic and p-value. If a significant difference is found, calculate Cohen's d effect size to measure the magnitude of the difference.

Previous independent samples t-test results indicated significant differences between deep learning teaching methods and traditional teaching methods in post-test scores (post-test scores, post-test deep learning levels, and post-test deep approach). The study calculated Cohen's d effect size to measure the magnitude of the difference, as shown in Table 21. A Cohen’s d value greater than 0.8 suggests a substantial difference in effect size between the two groups. Table 21 results demonstrated a practical significance in the effect size of deep learning teaching methods and traditional teaching methods on post-test scores (post-test scores, post-test deep learning levels, and post-test deep approach).

Table 21. Analysis of effectiveness indicators

analysis term	S^2 pooled (joint variance)	Cohen's *d* value
post-test score	65.380	0.936
Post-test deep learning level	84.118	2.606

5. Conclusion

This study conducted a quasi-experimental research at a selected vocational college. Initially, a variance analysis and multiple post hoc tests were performed on the final exam scores of four classes from the previous semester. Two classes with the most similar score distributions were selected as the control group and the experimental group for the quasi-experimental study. After selecting the two groups, the experimental group received deep learning teaching intervention, and the students' performance at the end of the semester was observed.

Initially, the study used the final exam scores from the previous semester as pre-test scores and measured the deep learning levels and deep approach values of both groups using a questionnaire before the experiment. Independent samples t-tests were conducted to confirm that there were no significant differences in deep learning levels and academic performance between the two classes in the experimental and control groups before the intervention, indicating a high degree of comparability.

Subsequently, to verify that there were no significant differences in scores for the control group students (traditional teaching method) between the two time points (pre and post-intervention), paired samples t-tests were used for analysis. The results showed no significant changes in deep learning levels for the control group students, while their academic performance showed a declining trend, suggesting that traditional teaching did not significantly enhance students' deep learning levels and academic performance.

Additionally, to validate that there were significant differences in scores for the experimental group students (deep learning teaching method) between the two time points, paired samples t-tests were also used for analysis. The results indicated a significant improvement in deep learning levels and academic performance for the experimental group students after the intervention, with scores significantly higher than before.

Furthermore, to confirm the significant differential effects of deep learning teaching methods (experimental group) and traditional teaching methods (control group) on students' scores in the post-test, independent samples t-tests were conducted for analysis. The results showed that the experimental group students scored significantly higher in post-test scores (deep learning levels and academic performance) compared to the control group students, demonstrating that deep learning teaching methods significantly improved students' post-test scores.

Finally, to further explore whether there was a practical significance in the size of the effects of deep learning teaching methods and traditional teaching methods on post-test scores, Cohen's d values were calculated. The results indicated that the Cohen's d values for both groups (post-test deep learning levels and post-test academic performance) were greater than 0.9, suggesting a practical significance in the size of the effects of deep learning teaching methods and traditional teaching methods on post-test scores.

6. Suggestions

The current study on the impact of deep learning teaching methods among computer science students in a higher vocational institution lays the foundation for future research directions. The researchers recommend expanding the investigation to include different academic year levels within the same major, allowing for a nuanced understanding of how the effects of deep learning approaches may vary across stages of the academic curriculum. Furthermore, extending the research to encompass students from diverse academic majors will contribute to assessing the generalizability of findings across disciplines with unique characteristics. Additionally, incorporating qualitative research methods, such as interviews and focus group discussions, will provide a richer understanding of students' experiences with deep learning, capturing subjective insights into the impact of these teaching methods on their learning processes. These suggested avenues for further investigation aim to enhance the comprehensiveness and applicability of insights gained from this study.

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