Generative AI in Vocational High School Design Cluster Practice Courses: Influences on Motivation and Effectiveness

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Abstract

In recent years, artificial intelligence (AI) technologies have rapidly advanced and found extensive applications in image design, text generation, and interactive media, increasingly being integrated into educational contexts. Among these technologies, generative AI characterized by real-time interactivity, multimodal content generation, and text-to-image conversion capabilities has demonstrated significant potential as an instructional tool in vocational high school design courses. However, empirical research on the integration of generative AI in vocational design education remains limited, and the effects on students' learning motivation and academic performance have yet to be thoroughly examined. This study investigates the impact of integrating generative AI on students' learning motivation and effectiveness in a computer graphics course at a vocational high school in Taiwan. An experimental design was employed, utilizing a cyclical learning model consisting of four stages: observation, summarization, questioning, and application. The course was conducted over two weeks, with three 50-minute sessions each week. Following the intervention, students completed an assessment of learning effectiveness and a questionnaire on learning motivation. Analysis using paired-sample t-tests, one-way ANOVA, and Pearson correlation revealed that the integration of generative AI significantly enhanced students' learning effectiveness. Although the gains in learning motivation were modest, the intervention resulted in tangible improvements in student learning effectiveness.

Keywords: generative AI, vocational high school, learning effectiveness, learning motivation

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Introduction

With the increasing maturity of AI technology, generative AI has emerged as a major focus in the education sector. Generative AI generates textual, graphical, and multimedia content using deep learning models and is characterized by real-time interaction and high levels of personalization. It is considered a significant opportunity for educational innovation (Wang, 2023). Both domestic and international studies have shown that generative AI tools, such as ChatGPT, can significantly enhance the efficiency of lesson preparation and provide students with personalized learning experiences. These tools effectively boost student engagement and motivation, thereby improving learning effectiveness (Hsu, 2024).

However, despite the growing prevalence of AI technology, systematic evaluations and empirical research on its effectiveness within the curriculum are still relatively limited. Most studies in AI education have concentrated on theoretical discussions or isolated case studies. There is a notable lack of large-scale, longitudinal empirical research examining the specific effects of AI technology on learning motivation and academic achievement in real educational settings (Holmes & Tuomi, 2022). Consequently, this study aims to investigate the impact of integrating generative AI into curriculum instruction on students' learning motivation and academic effectiveness.

Based on the background and motivation outlined above, the specific objectives of this study are as follows:

A. To examine the impact of integrating generative AI on the learning motivation of design students in technical high school professional practice courses.
B. To evaluate the learning effectiveness of integrating generative AI into these courses.
C. To investigate the relationship between learning motivation and learning effectiveness within the context of professional practice courses that integrate generative AI.

Literature Review

Current Development of Generative AI

The rapid advancement and widespread adoption of generative AI technology have positioned it as a significant driver of educational innovation worldwide. Generative AI (e.g., ChatGPT, DALL-E, etc.), which utilizes deep learning and big data, can automatically generate language, image, audio, and video content. It is increasingly being applied across various domains, including teaching, assessment, curriculum design, and personalized learning. These applications not only enhance the efficiency and flexibility of instruction but also facilitate the transformation of educational models (Xu, Taiping, 2024). Baidoo-Anu and Owusu Ansah (2023) have noted that the core value of generative AI lies in promoting individualized and adaptive teaching, allowing students to learn at their own pace and according to their specific needs. Meanwhile, teachers can leverage AI to assist with lesson preparation, assessment, and the development of diverse evaluation mechanisms, thereby improving teaching quality and student motivation. Sun and Zhou (2024) reported that the application of generative artificial intelligence can effectively improve the learning effectiveness of college students, providing empirical support for its role in higher education.

In addition, the use of generative AI tools in technical high schools and K-12 education is becoming increasingly prevalent. Research indicates that project-based learning, human-computer collaboration, and game-based curriculum design can significantly enhance students' cognitive, affective, and behavioral learning effectiveness (Yim & Su, 2024). Globally, many countries have prioritized AI literacy in educational development, actively incorporating AI into curricula at various educational levels and emphasizing the cultivation of cross-disciplinary competencies, including computational thinking, creativity, and digital citizenship (Ng et al., 2023).

ARCS Motivation Model

To address the prevalent issue of insufficient student motivation in classroom teaching, Keller (1987) proposed the ARCS Learning Motivation Model. This model emphasizes the systematic design of motivational strategies from the learner's perspective, encompassing four key components: Attention, Relevance, Confidence, and Satisfaction. The ARCS model is both logical and practice-oriented, aiding teachers in identifying and addressing factors that influence learning motivation and translating these insights into effective instructional strategies (Keller, 2010).

Julianingsih et al. (2023) demonstrated that teaching materials designed using the ARCS model effectively enhance students' motivation and academic performance in practical courses, particularly in technical high schools and application-oriented subjects. Contextualized questioning and exemplary teaching methods can significantly engage students' attention and interest. Furthermore, Fang et al. (2024) summarized that the ARCS model has emerged as one of the core theories in digital learning and cross-disciplinary educational research. It is widely employed for instructional design, the development of theoretical frameworks, and as a tool for measuring motivation in empirical studies across fields such as medicine, technology, and education.

Learning Effectiveness

Learning effectiveness refer to the comprehensive growth and performance of students in areas such as subject knowledge, cognitive development, psychosocial adaptation, attitudes, and values. According to Wang (2010), this concept is multi-level and integrated, encompassing both immediate knowledge acquisition and behavioral changes in the classroom (direct effectiveness) as well as long-term effects on career development and personal growth (indirect effectiveness). Learning effectiveness span cognitive, affective, and psychomotor domains and should be assessed at the institutional, curriculum, and classroom levels to fully evaluate the achievement of instructional objectives.

Internationally, the European Qualifications Framework (EQF) defines learning effectiveness in terms of knowledge, skills, and competencies, offering a standardized and internationally comparable system for assessing educational quality (European Commission, 2024). The OECD Learning Compass 2030 further underscores the significance of learning effectiveness that encompass student agency, reflective abilities, and real-world performance. It advocates for the use of diverse forms of evidence, such as portfolios and practical assessments, to evaluate comprehensive student development (OECD, 2023).

Recent research highlights the potential benefits of integrating generative AI into teaching and learning. Wei et al. (2025) found that generative AI tools, such as ChatGPT, facilitate iterative development and reflection during digital storytelling, resulting in significant improvements in the quality and creativity of students' final products. However, UNESCO (2023) warns that overreliance on AI may hinder the development of students' intellectual skills, emphasizing the need for a balance between AI-assisted learning and the cultivation of independent thinking.

In summary, learning effectiveness can be defined as the comprehensive demonstration of students' mastery of knowledge, application of skills, and transformation of attitudes through effective learning experiences. This mastery is evidenced by progress in subject assessments, creative practices, and reflective learning.

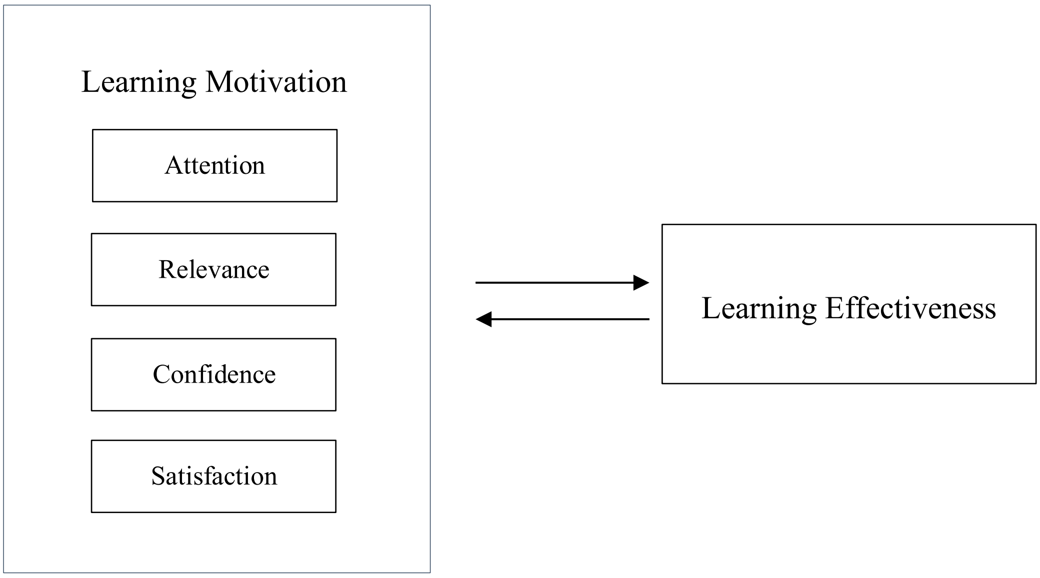
Research Design

This study aims to examine the correlation between students' learning motivation and learning effectiveness in the context of AI-integrated professional practice courses at technical high schools. Data was collected through a questionnaire survey. The following sections outline the research framework, target population, research instruments, and procedures for data processing and analysis.

Research Structure

According to the purpose of this study, the ARCS motivation model was adopted to investigate the relationship between motivation and the effectiveness of AI integration in professional practice courses for design students in technical high schools. The research framework is illustrated in Figure 1.

Figure 1
Research Structure



Research Subjects

This study employed convenience sampling to recruit second-year students from a technical high school in Tainan. The intervention involved the integration of generative AI into a computer graphic design applications course.

Research Tools

Learning Motivation Questionnaire

This study employed a questionnaire survey. Drawing on a synthesis of relevant literature, the Instructional Materials Motivation Survey (IMMS) developed by Keller (1987) served as the basis for instrument development. Additional factors identified in the literature concerning the integration of AI into curricula and students' learning motivation were incorporated into the design of the questionnaire. The instrument comprised 20 items distributed across four dimensions—Attention, Relevance, Confidence, and Satisfaction—with five items per dimension. Responses were rated on a five-point Likert scale (1 = strongly disagree, 5 = strongly agree), with higher scores reflecting greater learning motivation. The Cronbach's alpha coefficient was 0.974, indicating strong internal consistency.

Learning Effectiveness Evaluation

Learning effectiveness were assessed using a pre- and post-test design. The performance of students was compared before and after the integration of generative AI teaching materials. The evaluation employed a standardized scale ranging from 0 to 100, developed by the instructional staff.

Main Teaching Procedures

Based on the instructional framework designed by the instructor for integrating generative AI into teaching, the course adopts "The Application of AI in Design: Anti-Smoking Poster Design for a Friendly Campus" as its central theme. The curriculum incorporates generative artificial intelligence technologies to support students in the vocational high school design program in carrying out creative design practices. The total instructional time is three 50-minute sessions per week, implemented over a two-week period. The instructional framework employs a "Observation–Summarization–Questioning–Application" cyclical learning model, and through five sequential instructional units, systematically cultivates students' AI literacy and design competencies.

Data Analysis

In this study, the results of the questionnaires were compiled and processed using Excel software and statistically analyzed with JASP version 0.19.3. First, Cronbach's alpha coefficient was employed to assess the reliability of the questionnaire, while descriptive statistics were employed to present the mean and standard deviation for each item, as well as to summarize the demographic background of the sample. Second, the mean scores of students' learning motivation were ranked from highest to lowest and categorized based on their learning effectiveness scores. The total motivation scores for each group were then calculated. Differences in motivation scores between groups were analyzed using independent samples t-tests to determine statistical significance at the $p < .05$ level.

Additionally, a one-way ANOVA was conducted to examine the differences in learning motivation among various groups based on their learning effectiveness. This analysis aimed to understand the relationship between learning motivation and learning effectiveness for technical high school students enrolled in a generative AI-integrated professional practice course.

Research Results

This study analyzed data from both learning assessments and questionnaire surveys to explore the effects of integrating generative AI on learning motivation and effectiveness among design students in technical high schools. Additionally, it examined the motivational performance of students with varying levels of academic achievement.

Motivation of Students Integrating Generative AI Into the Curriculum

The overall mean score of students' learning motivation was 3.17, with all item means exceeding 3, indicating a moderately high level of motivation toward the integration of generative AI into the curriculum. Welch's *t*-test was further conducted to analyze gender differences across the four dimensions of the ARCS model. As presented in Table 2, male students scored significantly higher than female students in the Relevance, Confidence, and Satisfaction dimensions, suggesting that males outperformed females in these areas. Although the difference in the Attention dimension did not reach statistical significance, male students nonetheless achieved a higher mean score than their female counterparts.

Table 1
Summary of t-Tests on Learning Motivation of Students of Different Genders

Dimensions	Group	n	M	SD	t	p
A (Attention)	males	9	18.333	4.873	-1.363	0.198
	females	38	15.868	4.894		
R (Relevance)	males	9	19.222	3.420	-2.745**	0.013
	females	38	15.316	5.251		
C (Confidence)	males	9	20.111	2.472	-4.401***	< .001
	females	38	15.211	4.616		
S (Satisfaction)	males	9	19.444	2.297	-3.582***	< .001
	females	38	15.421	5.065		

Note. *p < .05, **p < . 01, ***p < . 001

Student Learning Effectiveness of Generative AI Integration in the Curriculum

First, this study employed a sample *t*-test to examine differences in students' learning effectiveness before and after the integration of generative AI into the curriculum. As shown in Table 3, the post-test mean (M = 81.57, SD = 10.77) was significantly higher than the pre-test mean (M = 68.21, SD = 14.61). The results indicated that the difference between the two was statistically significant ($p < .05$).

Therefore, for students in the technical high school design cohort, the integration of generative AI into instruction produced a significant improvement in learning effectiveness. This finding is consistent with the results of Sun and Zhou (2024), confirming that the application of generative AI in instructional design exerts a positive influence on learning performance.

Table 2
Summary Table of Effectiveness Scores Before and After AI Integration

	M	SD	t	df	p	95%CI LL	95%CI UL
Pre-AI	68.29	13.96	-7.29***	45	< .001	-1.418	-0.701
Post-AI	81.14	11.57					

Note. *p < .05, **p < .01, ***p < .001

Comparison of Students' Motivation for Generative AI-Integrated Courses by Learning Effectiveness

In this study, we aimed to further understand whether differences in learning motivation exist among students with varying learning effectiveness. The students' learning assessment scores (posttest scores) were categorized into three groups using the quartile method: high, medium, and low. A one-way analysis of variance (ANOVA) was conducted to examine the differences in the four dimensions of learning motivation patterns among students with different learning effectiveness based on the ARCS model. The ANOVA results indicated that there were no statistically significant differences in the four dimensions of the ARCS learning motivation model among students with varying learning effectiveness. Specifically, the results for each construct were as follows: Attention construct $F(2, 44) = 0.438$, $p > .05$; Relatedness construct $F(2, 44) = 0.007$, $p > .05$; Confidence construct $F(2, 44) = 0.167$, $p > .05$; Satisfaction construct $F(2, 44) = 0.027$, $p > .05$; Learning Motivation construct $F(2, 44) = 0.027$, $p > .05$; and overall motivation $F(2, 44) = 0.011$, $p > .05$. Additionally, Pearson’s cumulative correlation analyses presented in Table 7 revealed a weak negative correlation between motivation and learning effectiveness, which did not reach a statistically significant level ($r = -.198$, $p = .181$).

Taken together, the findings indicate that students with different levels of learning achievement did not exhibit significant differences across the four dimensions of the ARCS learning motivation model. Nevertheless, the overall integration of generative AI into the curriculum enhanced students’ learning motivation. Although the magnitude of improvement was modest, it still demonstrated a positive instructional effect.

Table 3
Summary of the Meaning and Standard Deviation of Students’ Learning Motivation in Different Learning Effectiveness

Dimensions	Performance Group	n	M	SD
Attention	Low	11	17.00	5.58
	Mid	30	16.43	4.40
	High	6	14.66	6.71
Relevance	Low	11	16.09	6.22
	Mid	30	16.10	4.66
	High	6	15.83	6.43

Confidence	Low	11	15.81	5.63
	Mid	30	16.06	4.37
	High	6	17.45	5.11
Satisfaction	Low	11	16.45	6.20
	Mid	30	16.06	4.60
	High	6	16.33	4.67
ARCS	Low	11	65.36	6.89
	Mid	30	64.66	3.11
	High	6	64.00	8.87

Table 4
ANCOVA of Motivation and Effectiveness

Dimensions	Source	SS	df	MS	F	p	Scheffé
Attention	Between	21.853	2	10.927	0.438	0.648	(1) > (2)
	Within	1098.700	44	24.970			(2) > (3)
	Total	1120.553	46				
Relevance	Between	0.366	2	0.183	0.007	0.993	(2) > (1)
	Within	1224.442	44	27.828			(1) > (3)
	Total	1224.808	46				
Confidence	Between	7.621	2	3.811	0.167	0.847	(3) > (2)
	Within	1004.336	44	22.826			(2) > (1)
	Total	1011.957	46				
Satisfaction	Between	1.349	2	0.675	0.027	0.974	(1) >(3)
	Within	1107.927	44	25.180			(3) > (2)
	Total	1109.276	46				
ARCS	Between	7.724	2	3.862	0.011	0.989	(1) > (2)
	Within	16037.212	44	364.482			(2) > (3)
	Total	16044.936	46				

Table 5
Summary Table of the Correlation Between the Cumulative Difference Between Learning Effectiveness and Learning Motivation

Variable		**Learning Motivation**	**Learning Effectiveness**
ARCS	Pearson’s r	-	
	p-value	-	
Learning Effectiveness	Pearson’s r	-0.198	-
	p-value	0.181	-

Conclusion and Recommendations

Conclusion

This study examined the relationship between learning motivation and learning effectiveness among design students in Taiwanese technical high schools who employed generative AI in their professional practice courses. The key findings are as follows:

1. Integrating generative AI into the curriculum has positively influenced students' motivation to learn, demonstrating a strong willingness to engage with this instructional method. Although no statistically significant differences were observed across the ARCS dimensions, students with lower performance effectiveness displayed relatively higher motivation compared to their high-achieving peers.
2. Generative AI integration has significantly improved student performance, as evidenced by notable increases in assessment scores. Students effectively employed generative AI tools and professional design software to enhance both the creativity and practicality of their work.
3. Following the integration of generative AI into technical high school design courses, no significant correlation was observed between students' learning motivation and their academic effectiveness. This finding may be attributed to the strong pre-existing competencies of high-achieving students, which led to a decreased reliance on AI assistance. In contrast, lower-achieving students benefited more noticeably from AI support, resulting in substantial gains in both motivation and performance. Therefore, while the integration of generative AI into design curricula shows promise, there is still room for improvement. It is recommended that future instructional practices align more closely with real-world applications to enhance both students' motivation and academic achievement simultaneously.

Recommendations

This study focused exclusively on learning motivation and the effectiveness resulting from the integration of generative AI in design practice courses. Future research should consider incorporating “learning satisfaction” as a third variable and analyze the interactions among motivation, effectiveness, and satisfaction. This approach will help determine whether AI integration can holistically enhance students’ sense of belonging and sustained engagement with the curriculum.

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