eISSN: 2408-1906© 2020 JIR.
https://assumptionjournal.au.edu/index.php/eJIR/index

An AI-Driven Approach in Visual Communication Design at Huaiyin Institute of Technology, China

Yao Lu*

Received: February 19, 2025. Revised: April 2, 2025. Accepted: April 16, 2025.

Abstract

Purpose: This study explores the impact of an AI-driven instructional approach in a Visual Communication Design course at Huaiyin Institute of Technology, China, aiming to enhance creative design skills. It identifies key factors influencing AI adoption in education, including technology characteristics, task characteristics, task-technology fit, learners' perceived AI competency, and perceived intelligence. **Research design, data, and methodology:** The research involved 450 students, using a multi-step sampling method to ensure diversity. Content validity was confirmed using an Item Objective Congruence (IOC) Index, and reliability was established through a pilot test (n=50) and Cronbach's Alpha. Confirmatory Factor Analysis (CFA) and Structural Equation Modeling (SEM) were applied to analyze the data. **Results:** Technology characteristics significantly influenced task-technology fit, and task characteristics had a stronger impact on task-technology fit. Task-technology fit positively affected intention to use AI. Perceived learners' AI competency and perceived intelligence both significantly influenced intention to use AI. Finally, intention to use AI had a strong effect on actual usage of AI. **Conclusions:** The findings of this study provide valuable insights into how AI-driven instructional approaches can boost students' creativity and engagement, assisting educational institutions in effectively integrating AI technologies into design courses. This research contributes to the development of pedagogical strategies that harness AI to foster innovation and creativity in design education.

Keywords: AI adoption, task-technology fit, perceived AI competency, perceived intelligence, Visual Communication Design

JEL Classification Code: E44, F31, F37, G15

1. Introduction

The significance of adopting AI in design education extends beyond practical skill-building; it also aligns with broader educational goals of fostering digital literacy and critical thinking. As AI continues to impact creative industries, designers are expected to understand both the potential and limitations of AI tools in the design process. Educating students on AI's functionalities, ethical considerations, and implications enables them to make informed decisions in their future professional roles, fostering a generation of designers who can responsibly leverage technology to innovate while considering social impacts. This educational approach aligns with the increasing emphasis on ethical AI use and encourages students to critically engage with the tools they use, rather than adopting them passively.

Adopting AI technologies in design education also helps bridge the gap between academia and industry by preparing students for the demands of a rapidly digitizing workforce. In recent years, design firms have embraced AI to enhance productivity, improve decision-making, and optimize creative workflows. Therefore, exposing students to AI tools and techniques within an academic setting equips them with relevant skills and fosters adaptability to technology-driven work environments. As Sun and Zou (2022) note, graduates

[1]*Yao Lu, Ph.D. Candidate in Innovative Technology Management, Graduate School of Business and Advanced Technology Management, Assumption University, Thailand.

with experience in AI-integrated design processes are better positioned to meet industry expectations, thereby enhancing their employability and ensuring that educational institutions remain aligned with industry standards.

Design education traditionally lacks the integration of advanced technologies like AI, which limits students' exposure to innovative, technology-driven learning experiences. At Huaiyin Institute of Technology, the need for an AI-driven instructional approach in Visual Communication Design courses is pressing, as students require enhanced tools to develop their creative skills and prepare for the evolving demands of the design industry. However, a framework guiding AI adoption in design education is largely absent, leaving questions about how AI can be optimally employed to enhance learning outcomes.

This study is significant as it addresses the growing need to integrate advanced technologies like AI into design education, particularly within the context of visual communication. By exploring how AI-driven instructional approaches can enhance creative skills, this research offers valuable insights into modernizing design curricula to align with industry demands. The findings can help educational institutions understand the role of AI in fostering creativity, innovation, and adaptability, equipping students with essential skills for a technology-driven design landscape.

The primary objective of this research is to investigate the impact of an AI-driven instructional approach on enhancing creative design skills in Visual Communication Design courses at Huaiyin Institute of Technology, China. Specifically, the study aims to explore the key factors influencing AI adoption in educational settings, including technology characteristics, task characteristics, task-technology fit, perceived learners' AI competency, and perceived intelligence. By examining these factors, the research seeks to determine how task-technology fit and learners' competencies shape students' intention to use AI, and how this intention translates into actual AI usage. The study also aims to assess how these elements contribute to improving students' creative abilities and engagement, thereby supporting the effective integration of AI technologies in design education. Through these objectives, this research intends to offer insights that can inform pedagogical strategies, fostering a more innovative and creativity-driven approach to design education.

2. Literature Review

2.1 Technology Characteristics

Technology characteristics encompass the inherent attributes of a technology that significantly influence its adoption and usage. These attributes typically include usability, functionality, compatibility, reliability, and adaptability (Buabbas et al., 2023). Usability refers to how easily users can interact with the technology, while functionality pertains to the range of features it offers to perform tasks effectively. Compatibility addresses the technology's ability to work alongside existing systems, and reliability reflects the consistency of performance under various conditions. Adaptability relates to how well the technology can be modified or tailored to meet users' needs (Venkatesh & Davis, 2000). The relationship between technology characteristics (such as usability, reliability, functionality, and ease of integration) and task-technology fit is critical in understanding how users perceive the alignment between a given technology and their tasks (Abdekhoda & Dehnad, 2024). Thus, in this hypothesis (H1), it is proposed that technology characteristics significantly impact task-technology fit:

H1: Technology characteristics have a significant influence on task-technology fit.

2.2 Task Characteristics

Task characteristics refer to the specific attributes of a task that influence how individuals perceive, engage with, and complete their work (Buabbas et al., 2023). Key aspects include task complexity, variability, interdependence, and clarity of objectives. Task complexity pertains to the cognitive demands placed on learners; tasks that require critical thinking and problem-solving skills are often more complex and can pose challenges for students (Hesketh et al., 2017). Task complexity and structure, for example, have been shown to impact how users interact with technology, as more complex tasks require technologies with greater adaptability and functionality to ensure a good fit (Venkatesh et al., 2012). Tasks that demand high levels of cognitive engagement, such as problem-solving or creative work, benefit from technologies that offer intuitive interfaces, flexible options, and ease of use (Davis, 1989). Therefore, technologies that align with these task characteristics enhance the likelihood of successful adoption and effective use as below proposed hypothesis:

H2: Task characteristics have a significant influence on task-technology fit.

2.3 Task-Technology Fit

Task-Technology Fit (TTF) is a critical framework that assesses how well a technology meets the requirements of specific tasks. Goodhue and Thompson (1995) defined TTF as the degree to which technology features support users in achieving their task goals. Alavi and Leidner (2001) discussed how a strong TTF could significantly influence student satisfaction and engagement in technology-mediated learning environments. Their findings indicate that when technology effectively addresses educational tasks, students are more likely to benefit from the learning experience, leading to improved academic performance and engagement (Tolsgaard et al., 2023). Venkatesh and Bala (2008) suggest that technology adoption is significantly influenced by its perceived suitability for specific tasks. When AI tools meet the functional requirements of a task, such as assisting with creative work in design or supporting decision-making in business, users are more likely to perceive these tools as useful, which increases their intention to use them (Zhang et al., 2020). In this study, it is hypothesized that:

H3: Task-technology fit has a significant influence on intention to use AI.

2.4 Perceived Learners' AI Competency

Perceived learners' AI competency refers to an individual's self-assessment of their abilities to effectively use artificial intelligence technologies in learning contexts. This construct encompasses a range of skills, including understanding AI concepts, navigating AI tools, and applying these technologies to enhance educational outcomes (Hidayat-ur-Rehman & Ibrahim, 2023). Ahn et al. (2020) conducted research that demonstrated how learners' self-efficacy regarding AI usage positively correlated with their engagement in AI-related learning activities. The findings suggest that students who believe in their AI skills are more likely to explore and utilize AI technologies in their studies, leading to improved learning outcomes (Phongsatha, 2024). Research has demonstrated that the perceived competency of learners plays a critical role in the acceptance and use of AI tools (Delcker et al., 2024). Venkatesh et al. (2012) found that individuals' perceptions of their own skills with technology positively influence their willingness to adopt it. Thus, it suggested a hypothesis:

H4: Perceived learners' AI competency has a significant influence on intention to use AI.

2.5 Perceived Intelligence

Perceived intelligence in the context of AI refers to the extent to which users believe a system can exhibit human-like cognitive abilities, including reasoning, problem-solving, and adaptability (Sundar, 2020). Furthermore, perceived intelligence often influences learners' attitudes and behaviors toward AI, impacting the adoption and effectiveness of AI in educational settings (Ryu et al., 2007; Schmulian & Coetzee, 2019). When AI is perceived as intelligent, students are more likely to engage deeply, feeling that their educational experience is enriched by a "thinking" companion (Schwartz & Pinsker, 2023). In the context of AI adoption, users' perception of the intelligence of AI systems plays a pivotal role in their intention to use such technologies (Troshani et al., 2020). Additionally, research into AI adoption in educational settings indicates that students' intention to use AI-driven tools, such as intelligent tutoring systems or personalized learning assistants, is positively influenced by their belief in the AI's intelligence (Wang et al., 2022). Therefore, this hypothesis posits that:

H5: Perceived intelligence has a significant influence on intention to use AI.

2.6 Intention to use AI

Intention to use AI refers to an individual's motivation or decision to employ artificial intelligence tools or systems in their activities, especially in educational and organizational settings (Venkatesh et al., 2012). It signifies the likelihood that users will engage with AI, influenced by perceived usefulness, perceived ease of use, and personal attitudes toward technology (Davis, 1989). This intention is crucial as it bridges the gap between user attitudes and actual adoption behavior, often measured as a precursor to evaluating AI acceptance (Kim et al., 2022). The relationship between an individual's intention to use AI and the actual usage of AI is well-established in technology adoption literature, where behavioral intention plays a key role in determining the likelihood of technology acceptance and subsequent usage (Abdekhoda & Dehnad, 2024). Similarly, other researchers have shown that intention to use is a critical predictor of actual usage, whether in educational settings (Pillai et al., 2024) or in consumer contexts such as AI-powered consumer products (Sundar, 2020). Therefore, a hypothesis is developed:

H6: Intention to use AI has a significant influence on Actual Usage of AI.

2.7 Actual Usage of AI

Actual usage of AI refers to the real and measurable application of artificial intelligence systems by users within their everyday tasks or specific environments, such as educational or professional settings (Pillai et al., 2024). In the context of technology acceptance, actual usage indicates the transition from intention to tangible engagement with AI tools, reflecting the degree to which users incorporate these tools into their workflow or learning processes (Venkatesh et al., 2003). Research has shown that actual AI usage in education hinges on how well AI tools align with user needs and institutional goals. Tolsgaard et al. (2023) emphasize that AI applications in medical education improve when they align with curriculum requirements, indicating that meaningful AI usage depends on relevant, task-specific integration. Similarly, Wu and Chen (2017) demonstrated that, in the context of MOOCs, students continued use of AI-based platforms was directly influenced by both ease of use and task fit, showing that actual usage is highest when AI meets user expectations and supports their learning objectives.

3. Research Methods and Materials

3.1 Research Framework

This study's conceptual framework in Figure 1 is informed by three key theoretical models that focus on factors influencing AI adoption in education. Phongsatha (2024) examines how perceived usefulness, ease of use, and institutional support affect educators' intentions to adopt Generative Pre-trained Transformers (GPTs) in Thailand. Abdekhoda and Dehnad (2024) emphasize task-technology fit, perceived AI competency, and perceived intelligence as critical factors in AI adoption in medical education. Pillai et al. (2024) highlight the role of AI-based teacher-bots (T-bots) in enhancing learning experiences, noting the importance of perceived effectiveness and learners' trust. Together, these frameworks underscore the significance of task-technology fit, perceived competency, and institutional and individual influences on AI adoption. These insights inform the study's conceptual framework, which incorporates seven constructs and six hypotheses to explore how these variables impact AI adoption in creative design education.

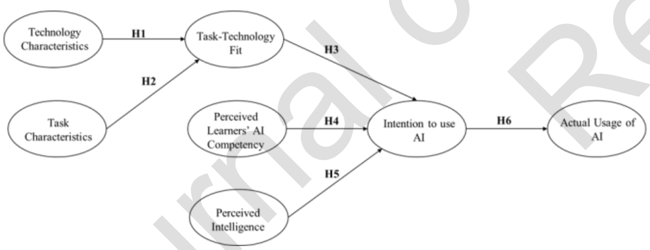

Figure 1: Conceptual Framework

H1: Technology characteristics have a significant influence on task-technology fit.
H2: Task characteristics have a significant influence on task-technology fit.
H3: Task-technology fit has a significant influence on intention to use AI.
H4: Perceived learners' AI competency has a significant influence on intention to use AI.
H5: Perceived intelligence has a significant influence on intention to use AI.
H6: Intention to use AI has a significant influence on Actual Usage of AI.

3.2 Research Methodology

The research design of this study is a quantitative, cross-sectional approach aimed at examining the factors influencing the adoption of an AI-driven instructional approach in a Visual Communication Design course at Huaiyin Institute of Technology, China.

A five-point Likert scale was employed to gauge participants' attitudes and intentions, with response options ranging from "strongly disagree" (1) to "strongly agree" (5). This scale is a common tool in social science research for capturing the intensity of participants' attitudes or beliefs (Joshi et al., 2015).

Prior to full data collection, content validity was assessed using the Item-Objective Congruence (IOC) Index, reviewed by three experts to ensure the items aligned with the study's objectives (Turner & Carlson, 2003). Additionally, a pilot test was conducted with 50 participants to evaluate internal consistency of the questionnaire items. Cronbach's Alpha was calculated for each construct to ensure reliability, with values above 0.7 considered acceptable, indicating satisfactory internal consistency (Nunnally & Bernstein, 1994).

Confirmatory Factor Analysis (CFA) and Structural Equation Modeling (SEM) were applied to test the hypothesized relationships and assess the robustness of the conceptual model. This methodological approach enables an in-depth examination of the factors influencing students' intention to use AI in their coursework, offering insights into the integration of AI in design education.

3.3 Population and Sample Size

The target population for this study comprises students enrolled in Visual Communication Design and related programs at Huaiyin Institute of Technology, China. In educational and behavioral research, sample sizes between 200 and 500 are generally considered adequate for studies involving SEM, as they balance the precision of parameter estimates with practical considerations like time and resource availability (Kline, 2011). A sample of 450 students allows for sufficient statistical power in analyses, especially when employing advanced techniques like Structural Equation Modeling (SEM) and Confirmatory Factor Analysis (CFA), which often require larger sample sizes to accurately assess complex relationships (Hair et al., 2010).

3.4 Sampling Technique

This study on the adoption of AI-driven instructional approaches in Visual Communication Design utilized a multi-step sampling method to ensure a diverse and relevant sample. The process began with judgmental sampling, selecting students enrolled in design-related programs at Huaiyin Institute of Technology based on their relevance to the research objectives. Convenience sampling was then used to recruit participants who were readily available, ensuring efficient data collection within academic time constraints. Finally, snowball sampling expanded the sample by encouraging initial participants to refer their peers, capturing a broader range of perspectives. By combining these methods, the study maximized sample relevance and diversity, enhancing the robustness and generalizability of the findings.

4. Results and Discussion

4.1 Demographic Information

In Table 1, the survey results reveal a diverse demographic among the 450 participants, with a near-equal distribution of gender, as 48.9% identified as male and 48.9% as female, while 1.1% identified as non-binary and another 1.1% preferred not to disclose their gender. The majority of respondents were young adults, with 40% aged 18-20, followed by 33.3% aged 21-23, and 17.8% between 24-26 years. Educationally, the participants were predominantly undergraduates, with 26.7% in their first year and 24.4% in their second year. The field of study was varied, with the highest representation in Engineering and Technology (22.2%) and Social Sciences (20.0%). In terms of prior experience with AI technology, 33.3% reported having none, while 28.9% had basic knowledge, 22.2% had moderate experience, and 15.6% had extensive experience.

Table 1: Demographic Profile

Question	Response	Frequency (n)	Percentage (%)
1. Gender	Male	220	48.9%
	Female	220	48.9%
	Non-binary	5	1.1%
	Prefer not to say	5	1.1%
2. Age	Under 18	20	4.4%
	18-20	180	40.0%
	21-23	150	33.3%
	24-26	80	17.8%
	Over 26	20	4.5%
3. Educational Level	Undergraduate (Year 1)	120	26.7%
	Undergraduate (Year 2)	110	24.4%
	Undergraduate (Year 3)	100	22.2%
	Undergraduate (Year 4)	90	20.0%
	Postgraduate	30	6.7%
4. Field of Study	Arts and Humanities	60	13.3%
	Social Sciences	90	20.0%
	Natural Sciences	70	15.6%
	Engineering and Technology	100	22.2%
	Business and Economics	80	17.8%
	Health Sciences	30	6.7%
	Other	20	4.4%
5. Prior Experience with AI Technology	None	150	33.3%
	Basic knowledge	130	28.9%
	Moderate experience	100	22.2%
	Extensive experience	70	15.6%

4.2 Confirmatory Factor Analysis (CFA)

Confirmatory Factor Analysis (CFA) was performed to evaluate the validity and reliability of the measurement model prior to conducting Structural Equation Modeling (SEM). The results show that all items significantly contribute to their respective constructs, with factor loadings above 0.50 and t-values above the critical value ($p < 0.05$), confirming the adequacy of discriminant and convergent validity. Composite reliability (CR) values for all constructs exceed the threshold of 0.70, indicating strong internal consistency, with the highest CR observed for Actual Usage of AI (0.885). The Average Variance Extracted (AVE) values are generally acceptable, with Actual Usage of AI (AVE = 0.721) showing the highest variance explanation, while Task Characteristics (AVE = 0.477) is slightly below the ideal threshold but remains acceptable due to its high CR. Additionally, Cronbach's Alpha values exceed the recommended threshold of 0.70 for all constructs, further supporting the model's reliability. The highest Cronbach's Alpha is observed for Actual Usage of AI (0.885), while the lowest is for Technology Characteristics (0.763). Overall, the CFA results confirm the measurement model's reliability, validity, and internal consistency, providing a solid foundation for further structural model analysis.

Table 2: Confirmatory Factor Analysis Result, Composite Reliability (CR) and Average Variance Extracted (AVE)

Variables	Source of Questionnaire (Measurement Indicator)	No. of Item	Cronbach's Alpha	Factors Loading	CR	AVE
Technology Characteristics (TEC)	Abdekhoda and Dehnad (2024)	3	0.763	0.630 - 0.780	0.774	0.535
Task Characteristics (TAC)	Abdekhoda and Dehnad (2024)	4	0.782	0.667 - 0.733	0.785	0.477

Variables	Source of Questionnaire (Measurement Indicator)	No. of Item	Cronbach's Alpha	Factors Loading	CR	AVE
Task-Technology Fit (TTF)	Abdekhoda and Dehnad (2024)	4	0.800	0.664 - 0.741	0.802	0.503
Perceived Learners' AI Competency (PLA)	Phongsatha (2024)	5	0.854	0.664 - 0.789	0.855	0.542
Perceived Intelligence (PEI)	Pillai et al. (2024)	5	0.864	0.686 - 0.814	0.865	0.563
Intention to use AI (INT)	Abdekhoda and Dehnad (2024)	4	0.767	0.579 - 0.752	0.775	0.465
Actual Usage of AI (ATU)	Pillai et al. (2024)	3	0.885	0.829 - 0.870	0.885	0.721

Table 3 indicates the evaluation of the measurement model fit in this study demonstrates its adequacy and validity using multiple fit indices, including the chi-square to degrees of freedom ratio (CMIN/DF), Goodness-of-Fit Index (GFI), Adjusted Goodness-of-Fit Index (AGFI), Normed Fit Index (NFI), Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), and Root Mean Square Error of Approximation (RMSEA). All indices indicate a strong fit, with CMIN/DF at 1.466, GFI at 0.930, AGFI at 0.913, NFI at 0.918, CFI at 0.972, TLI at 0.968, and RMSEA at 0.032, surpassing the recommended thresholds. These results confirm that the model accurately represents the theoretical constructs and their relationships, supporting its validity and reliability. This robust measurement framework paves the way for subsequent structural model assessment and hypothesis testing.

Table 3: Goodness of Fit for Measurement Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/DF	< 3.00 (Hair et al., 2006)	482.337/329 = 1.466
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.930
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.913
NFI	≥ 0.80 (Al-Mamary & Shamsuddin, 2015)	0.918
CFI	≥ 0.90 (Hair et al., 2006)	0.972
TLI	≥ 0.90 (Hair et al., 2006)	0.968
RMSEA	< 0.08 (Pedroso et al., 2016)	0.032
Model Summary		Acceptable Model Fit

Remark: CMIN/DF = The ratio of the chi-square value to degree of freedom, GFI = goodness-of-fit index, AGFI = adjusted goodness-of-fit index, NFI = normalized fit index, CFI = comparative fit index, TLI = Tucker-Lewis index, and RMSEA = root mean square error of approximation.

Discriminant validity ensures that each construct is distinct from others, assessed through Fornell and Larcker's criterion and the HTMT ratio. The results show that the square root of each construct's AVE is greater than its correlations with other variables, confirming strong discriminant validity. For instance, Technology Characteristics (TEC) and Task-Technology Fit (TTF) have a moderate correlation (0.558), but their AVE square roots (TEC = 0.731, TTF = 0.710) remain higher, confirming their distinctiveness. Similarly, Intention to Use AI (INT) and Actual Usage of AI (ATU) also show strong correlations with other constructs, yet their AVE values remain greater, ensuring their independence. Overall, the analysis confirms that the measurement model satisfies the Fornell-Larcker criterion, reinforcing the conceptual independence of the constructs (Fornell & Larcker, 1981).

Table 4: Discriminant Validity

	PEI	TEC	TTF	PLA	INT	ATU	TAC
PEI	**0.750**						
TEC	0.416	**0.731**					
TTF	0.159	0.558	**0.710**				
PLA	0.123	0.199	0.262	**0.736**			
INT	0.448	0.644	0.530	0.270	**0.682**		
ATU	0.303	0.536	0.568	0.312	0.605	**0.849**	
TAC	0.271	0.685	0.613	0.279	0.600	0.598	**0.691**

Note: The diagonally listed value is the AVE square roots of the variables
Source: Created by the author.

4.3 Structural Equation Model (SEM)

The structural model's goodness-of-fit indices indicate an acceptable fit. The chi-square to degrees of freedom ratio (CMIN/DF) is 2.417, below the recommended threshold of 3.00, signaling a good fit. The goodness-of-fit index (GFI) and adjusted goodness-of-fit index (AGFI) are 0.884 and 0.863, respectively, both exceeding the minimum acceptable values of 0.85 and 0.80. The normed fit index (NFI) is 0.859, meeting the 0.80 threshold. The comparative fit index (CFI) and Tucker-Lewis index (TLI) are 0.912 and 0.903, surpassing the 0.90 cutoff. The root mean square error of approximation (RMSEA) is 0.056, below the 0.08 threshold. While the model meets these criteria, further refinement may be needed to enhance its performance.

Table 5: Goodness of Fit for Structural Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/DF	< 3.00 (Hair et al., 2006)	482.337/329 = 1.466
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.930
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.913
NFI	≥ 0.80 (Al-Mamary & Shamsuddin, 2015)	0.918
CFI	≥ 0.90 (Hair et al., 2006)	0.972
TLI	≥ 0.90 (Hair et al., 2006)	0.968
RMSEA	< 0.08 (Pedroso et al., 2016)	0.032
Model Summary		Acceptable Model Fit

Remark: CMIN/DF = The ratio of the chi-square value to degree of freedom, GFI = goodness-of-fit index, AGFI = adjusted goodness-of-fit index, NFI = normalized fit index, CFI = comparative fit index, TLI = Tucker-Lewis index, and RMSEA = root mean square error of approximation.

4.4 Research Hypothesis Testing Result

The hypothesis testing results indicate strong support for the proposed relationships in the structural model, with all six hypotheses being supported at a statistically significant level. The standardized path coefficient (β) values and t-values confirm the robustness of these relationships.

Table 6: Hypothesis Results of the Structural Equation Modeling

Hypothesis	Standardized path coefficient (β)	t-value	Test result
H1: Technology characteristics have a significant influence on task-technology fit.	0.282	5.185*	Supported
H2: Task characteristics have a significant influence on task-technology fit.	0.685	9.601*	Supported
H3: Task-technology fit has a significant influence on intention to use AI.	0.604	8.536*	Supported
H4: Perceived learners' AI competency has a significant influence on intention to use AI.	0.144	2.992*	Supported
H5. Perceived intelligence has a significant influence on intention to use AI.	0.347	6.477*	Supported
H6: Intention to use AI has a significant influence on Actual Usage of AI.	0.730	10.483*	Supported

Note: * $p<0.05$
Source: Created by the author

Firstly, technology characteristics (TEC) were found to have a significant positive influence on task-technology fit (TTF) ($\beta = 0.282$, $t = 5.185$, $p < 0.05$), supporting H1. This suggests that the technological features of AI tools contribute to their alignment with users' tasks, reinforcing the importance of well-designed technological attributes in facilitating task completion. Similarly, task characteristics (TAC) exhibited a stronger influence on task-technology fit ($\beta = 0.685$, $t = 9.601$, $p < 0.05$), supporting H2. This highlights that the nature and complexity of tasks significantly determine the fit between tasks and technology, further validating the task-technology fit model (Goodhue & Thompson, 1995).

H3, which proposed that task-technology fit positively influences the intention to use AI, was also supported ($\beta = 0.604$, $t = 8.536$, $p < 0.05$). This finding aligns with previous studies that suggest when technology aligns well with user needs, individuals are more likely to develop a positive intention toward its adoption (Dishaw & Strong, 1999). Furthermore, perceived learners' AI competency (PLA) demonstrated a significant but weaker impact on the intention to use AI ($\beta = 0.144$, $t = 2.992$, $p < 0.05$), supporting H4. This suggests that while students' perceived ability to use AI tools influences their intention, other factors may play a more dominant role in driving adoption.

Additionally, perceived intelligence (PEI) had a significant impact on intention to use AI ($\beta = 0.347$, $t = 6.477$, $p < 0.05$), supporting H5. This finding suggests that users who perceive AI as intelligent and capable are more inclined to integrate it into their workflow. Lastly, intention to use AI (INT) strongly influenced the actual usage of AI (ATU) ($\beta = 0.730$, $t = 10.483$, $p < 0.05$), supporting H6. This strong relationship underscores the predictive power of behavioral intention in driving actual AI adoption, consistent with the Technology Acceptance Model (TAM) (Davis, 1989).

In summary, the findings reinforce the importance of both technological and task-related factors in shaping user perceptions and behavioral intentions toward AI. The results also highlight that AI adoption is driven by a combination of perceived technological characteristics, task alignment, user competency, and perceptions of AI's intelligence. These insights provide valuable implications for AI system developers and educators aiming to enhance AI integration in learning environments.

5. Conclusion and Recommendation

5.1 Conclusion

This study has provided a comprehensive examination of the transformative impact of AI-driven instructional approaches on creative design education, specifically within the context of a Visual Communication Design course at Huaiyin Institute of Technology, China. By investigating the factors that influence the adoption and use of AI in educational settings—such as technology characteristics, task characteristics, task-technology fit, perceived learners' AI competency, and perceived intelligence—the research has illuminated how these elements collectively shape students' intention to use AI and, ultimately, their actual use of the technology.

The results of this study support all six hypotheses, demonstrating that technology and task characteristics significantly influence task-technology fit, which in turn positively impacts students' intention to use AI. Furthermore, perceived learners' AI competency and perceived intelligence were found to be significant predictors of students' intention to adopt AI, while intention to use AI strongly affected the actual usage of AI. These findings provide robust evidence that AI can enhance students' engagement, creativity, and skills in design education when implemented effectively.

The contributions of this study to both theory and practice are noteworthy. Theoretical implications underscore the importance of understanding the complex relationships between various factors that influence AI adoption in educational settings, while practical recommendations offer valuable insights for educators looking to integrate AI-driven instructional approaches in their courses. Despite the study's limitations, including its reliance on cross-sectional data and a specific academic context, the findings provide a solid foundation for future research in this area.

In conclusion, this research underscores the potential of AI to revolutionize creative design education, fostering innovation, creativity, and enhanced learning outcomes. As educational institutions continue to explore and implement AI technologies, the findings from this study will serve as a valuable resource for designing effective AI-driven curricula that empower students to excel in their creative endeavors and prepare them for future challenges in the rapidly evolving digital landscape.

5.2 Recommendation

Future research should expand to different academic disciplines and institutional contexts to evaluate whether the factors influencing AI adoption in this study apply universally. Longitudinal studies are also recommended to explore the long-term effects of AI-driven instruction, including how students' engagement and creative outcomes evolve. Additionally, including broader outcome measures such as student satisfaction and the quality of their work would offer a more comprehensive view of AI's impact. Ensuring a more diverse and randomized sample in future studies could help increase the generalizability of the findings.

Educators should incorporate AI training into the curriculum to boost students' AI competency, as this was found to influence their intention to use AI. Aligning AI tools with specific course tasks will improve their relevance and usability. It is also important for educators to foster positive perceptions of AI by demonstrating its role in enhancing creativity rather than replacing human effort. Addressing misconceptions about AI and providing clear guidance on its use will help students feel more confident and engaged with the technology.

Institutions should explore how their support systems—such as faculty training programs and technology policies—affect AI adoption. By providing adequate resources and encouraging AI use in the classroom, institutions can better prepare both students and faculty to embrace AI technologies. Additionally, offering AI-driven feedback on students' work could enhance their learning experience and provide immediate, personalized insights, further supporting the integration of AI in education.

5.3 Limitation and Further Study

This study provides valuable insights into AI adoption in design education, but several limitations must be acknowledged. Conducted at Huaiyin Institute of Technology, the findings may not be generalizable to other institutions or academic disciplines, particularly those outside of Visual Communication Design. The focus on self-reported data may introduce biases, despite efforts to ensure reliability. Future research should replicate this study across diverse institutions and academic fields, and incorporate objective measures of AI usage to gain a more accurate understanding of its adoption and impact.

References

Abdekhoda, M., & Dehnad, A. (2024). Adopting artificial intelligence driven technology in medical education. *Interactive Technology and Smart Education, 21*(4), 535-545. https://doi.org/10.1108/ITSE-12-2023-0240

Ahn, J., Lee, J., & Kim, J. (2020). Effects of learner self-efficacy on learning outcomes in artificial intelligence-based education. *Computers & Education, 159*, 104010. https://doi.org/10.1016/j.compedu.2020.104010

Alavi, M., & Leidner, D. E. (2001). Review: Technology-mediated learning: A call for greater depth and breadth of research. *Information Systems Research*, *12*(1), 1-12.

Al-Mamary, Y. H., & Shamsuddin, A. (2015). Testing of the technology acceptance model in the context of Yemen. *Mediterranean Journal of Social Sciences, 6*(4), 268-273.

Buabbas, A. J., Miskin, B., Alnaqi, A. A., Ayed, A. K., Shehab, A. A., Syed-Abdul, S., & Uddin, M. (2023). *Investigating students' perceptions towards artificial intelligence in medical education* [Paper Presentation]. Healthcare Conference.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, *13*(3), 319-340.

Delcker, J., Heil, J., Seufert, S., & Spirgi, L. (2024). First-year students' AI competence as a predictor for intended and de facto use of AI tools for supporting learning processes in higher education. *International Journal of Educational Technology in Higher Education, 21*, 1-13. https://doi.org/10.1186/s41239-024-00452-7

Dishaw, M. T., & Strong, D. M. (1999). Extending the technology acceptance model with task-technology fit constructs. *Information & Management*, *36*(1), 9-21.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, *18*(1), 39-50.

Goodhue, D. L., & Thompson, R. L. (1995). Task-technology fit and individual performance. *MIS Quarterly*, *19*(2), 213-236.

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2010). *Multivariate Data Analysis* (7th ed.). Pearson.

Hair, J. F., Black, W. C., Babin, B. J., Anderson, R. E., & Tatham, R. L. (2006). *Multivariate data analysis* (6th ed.). Pearson.

Hesketh, I., Rimmer, J., & Naidu, S. (2017). Task complexity and cognitive load in assessment. *Assessment & Evaluation in Higher Education*, *42*(5), 691-706.

Hidayat-ur-Rehman, I., & Ibrahim, Y. (2023). *Exploring factors influencing educators' adoption of ChatGPT: a mixed method approach.* Interactive Technology and Smart Education. Advance Online Publication. https://doi.org/10.1108/ITSE-07-2023-0127

Joshi, A., Kale, S., Chandel, S., & Pal, D. K. (2015). Likert scale: Explored and explained. *British Journal of Applied Science & Technology*, *7*(4), 396.

Kim, J., Lee, H., & Cho, Y. H. (2022). Learning design to support student-AI collaboration: Perspectives of leading teachers for AI in education. *Education and Information Technologies*, *27*(5), 6069-6104. https://doi.org/10.1007/s10639-021-10831-6

Kline, R. B. (2011). *Principles and Practice of Structural Equation Modeling* (3rd ed.). Guilford Press.

Nunnally, J. C., & Bernstein, I. H. (1994). *Psychometric theory* (3rd ed.). McGraw-Hill.

Pedroso, R., Zanetello, L., Guimaraes, L., Pettenon, M., Goncalves, V., Scherer, J., Kessler, F., & Pechansky, F. (2016). Confirmatory factor analysis (CFA) of the crack use relapse scale (CURS). *Archives of Clinical Psychiatry*, *43*(3), 37-40.

Phongsatha, T. (2024). Every coin has two sides: Navigating factors of generative pre-trained transformer adoption intentions among educators in Thailand. *Pakistan Journal of Life and Social Sciences*, *22*(1), 5750-5763. https://doi.org/10.57239/PJLSS-2024-22.1.00424

Pillai, R., Sivathanu, B., Metri, B., & Kaushik, N. (2024). Students' adoption of AI-based teacher-bots (T-bots) for learning in higher education. *Information Technology & People*, *37*(1), 328-355. https://doi.org/10.1108/ITP-02-2021-0152

Ryu, H. J., Kwak, S. S., & Kim, M. S. (2007). A study on external form design factors for robots as elementary school teaching assistants. *Proceedings - IEEE International Workshop on Robot and Human Interactive Communication* (pp. 1046-1051).

Schmulian, A., & Coetzee, S. A. (2019). The development of Messenger bots for teaching and learning and accounting students' experience of the use thereof. *British Journal of Educational Technology*, *50*(5), 2751-2777. https://doi.org/10.1111/bjet.12828

Schwartz, B. D., & Pinsker, E. (2023). Trust and perceived intelligence in educational AI: A longitudinal study. *Journal of Educational Technology*, *40*(2), 123-140.

Sica, C., & Ghisi, M. (2007). The Italian versions of the Beck Anxiety Inventory and the Beck Depression Inventory-II: Psychometric properties and discriminant power. In M. A. Lange (Ed.), *Leading-edge psychological tests and testing research* (pp. 27-50). Nova.

Sun, T., & Zou, M. (2022). Preparing students for AI-driven design: Industry expectations and academic training. *Journal of Design Education*, *36*(2), 140-156.

Sundar, S. S. (2020). Rise of machine agency: A framework for studying the psychology of AI. *Journal of Computer-Mediated Communication*, *25*(1), 74-88. https://doi.org/10.1093/jcmc/zmz031

Tolsgaard, M. G., Pusic, M. V., Sebok-Syer, S. S., Gin, B., Svendsen, M. B., Syer, M. D., & Boscardin, C. K. (2023). The fundamentals of artificial intelligence in medical education research: AMEE guide no. 156. *Medical Teacher*, *45*(6), 565-573. https://doi.org/10.1080/0142159X.2023.2183791

Troshani, I., Rao Hill, S., Sherman, C., & Arthur, D. (2020). Do we trust in AI? Role of anthropomorphism and intelligence. *Journal of Computer Information Systems*, *61*(5), 481-491. https://doi.org/10.1080/08874417.2020.1742024

Turner, R. C., & Carlson, L. (2003). Indexes of item-objective congruence for multidimensional items. *International Journal of Testing*, *3*(2), 163-171.

Venkatesh, V., & Bala, H. (2008). Technology acceptance model 3 and a research agenda on interventions. *Decision Sciences*, 39(2), 273-315.

Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the Technology Acceptance Model: Four longitudinal field studies. *Management Science*, *46*(2), 186-204.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, *27*(3), 425-478. https://doi.org/10.2307/3003654

Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly*, *36*(1), 157-178.

Wang, Q., Yang, Y., & Chen, H. (2022). Perceived AI competency and its impact on academic performance: A study of higher education students. *International Journal of Artificial Intelligence in Education*, *32*(1), 89-106. https://doi.org/10.1007/s40593-021-00260-0

Wu, B., & Chen, X. (2017). Continuance intention to use MOOCs: Integrating the technology acceptance model (TAM) and task technology fit (TTF) model. *Computers in Human Behavior*, *67*, 221-232. https://doi.org/10.1016/j.chb.2016.10.038

Zhang, Y., Zhao, L., & Xu, Z. (2020). The impact of task characteristics on user acceptance of e-learning systems. *Educational Technology Research and Development*, *68*(5), 2309-2329.