



The Instructors' Perceptions toward AI Teaching: Product Design Major at Shandong University

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Abstract

Background and Aims: This study examined instructors' perceptions of applying artificial intelligence (AI) in teaching product design at universities in Shandong Province, China. It drew on the Technology Acceptance Model (TAM), examining perceived usefulness, perceived ease of use, self-efficacy, interest, stress, and training as constructs influencing AI adoption in higher education.

Methodology: A mixed-methods design was employed. Quantitative data were collected from 208 product design instructors through a structured questionnaire and analysed using AMOS and structural equation modelling (SEM). Qualitative data were gathered through in-depth interviews with 15 instructors and analysed thematically in NVivo. The thematic analysis surfaced instructors' general optimism toward AI, the sources of teaching-related pressure, the perceived shortage of discipline-specific training, and concerns about over-reliance on AI. Informed consent and confidentiality were maintained throughout the study.

Results: Instructors generally held positive attitudes toward using AI in teaching. Self-efficacy, interest, and stress were positively associated with perceived usefulness and perceived ease of use, with stress the strongest predictor, followed by self-efficacy and interest. Training was positively associated with attitudes toward use. The qualitative findings corroborated these patterns: instructors described AI as improving lesson-



preparation efficiency, while cautioning that over-reliance could weaken creativity and self-reflection, and noting that most available training targets other disciplines rather than product design.

Conclusion: Strengthening AI-related training and capacity building for product design instructors is recommended to lower teaching costs and improve the effective use of AI in pedagogy. Discipline-specific characteristics of product design, including tool-oriented thinking and interdisciplinary openness, further facilitate AI adoption in this field.

Keywords: AI teaching; product design; instructors' perceptions; Technology Acceptance Model

Introduction

The rapid development of artificial intelligence (AI) is reshaping higher education, offering new ways to design instruction, personalise learning, and manage teaching resources (Zhang & Aslan, 2021). Yet the benefits of AI in the classroom depend less on the technology itself than on the educators who decide whether and how to use it. International policy bodies have made this point explicitly: UNESCO (2023) reports that fewer than ten percent of schools and universities have formal guidance on generative AI, and the Beijing Consensus and subsequent UNESCO and OECD frameworks identify teacher capacity and training as decisive conditions for effective, sustainable adoption (OECD, 2020; UNESCO, 2019, 2023). Teachers, in other words, are the pivotal actors in AI integration, and their readiness cannot be assumed.

This challenge is especially acute in design education. Design teaching has always evolved with its tools, yet AI has not been deeply or systematically integrated into art and design instruction (Kong, 2020). Because the technology changes so quickly, there is limited understanding of how it will reshape design classrooms, and comparatively little research has examined design teachers' own insights, experiences, and attitudes toward AI (Vartiainen & Tedre, 2023). Since instructors are central to student learning, understanding how they perceive AI—and what shapes those perceptions—is a prerequisite for meaningful adoption.



China has prioritised AI in education and is extending it into higher education (Yang, 2019), and design schools have begun to debate AI's role in future-oriented curricula. Product design is a particularly informative case: as a tool-dependent, interdisciplinary field, it may be unusually receptive to AI, yet the perceptions of product design instructors specifically—and the factors that drive or inhibit their acceptance—remain largely unexamined, particularly in regional contexts such as Shandong Province. This study addresses that gap by examining product design instructors' perceptions of AI in teaching, the factors influencing those perceptions, and the means by which adoption can be promoted.

Objectives

1. To investigate instructors' perceptions of AI in teaching product design at universities in Shandong Province, China.
2. To identify the factors influencing instructors' use of AI in teaching product design.
3. To determine methods for promoting the use of AI in teaching product design at universities in Shandong Province.

Literature Review

This review is organised thematically around four bodies of work—AI in higher education, AI in design and art education, technology-acceptance research, and instructor adoption of AI—before justifying the Technology Acceptance Model (TAM) as the study's framework.

AI in higher education

Research on AI in higher education has expanded rapidly but unevenly. Systematic reviews show that AI teaching and learning was historically concentrated in computer-science programmes and has only recently spread across disciplines (Ng et al., 2023). Reviews of university-level work between 2019 and 2023 conclude that AI creates both opportunities and disruptions, prompting calls to rethink the purpose of education rather than simply adopt new tools (López-Regalado et al., 2024). The arrival of



generative tools such as ChatGPT sharpened these debates, pushing universities to redesign courses around critical thinking and to reconsider assessment so as to balance technological assistance with human creativity (Huang, 2023). Across these studies, a recurring conclusion is that the value of AI depends on how educators integrate it, and that rapid technological change continually reopens questions earlier research had seemed to settle (Chen et al., 2020).

AI in design and art education

Within design and art education, AI is frequently described as a powerful but under-utilised tool. Studies of computer-aided art teaching report clear efficiency and quality gains over traditional models (He & Sun, 2021), and AI-supported computer-aided design (CAD) is increasingly treated as a mainstream mode of creative production (Wang & Wu, 2024). At the same time, Kong (2020) argues that AI has not been applied in depth to art teaching and proposes strategies to expand its adaptability and strengthen the intelligent teaching model. More conceptually, Verganti et al. (2020) reframe AI as shifting design work from problem-solving toward sense-making. Taken together, this literature suggests substantial promise for AI in design education alongside a persistent gap between its potential and its actual classroom use—precisely the gap in which instructor perceptions become decisive.

Technology-acceptance research and the TAM

To explain why individuals adopt or resist a technology, researchers have long relied on the Technology Acceptance Model (TAM). Proposed by Davis in 1989, TAM holds that two beliefs—perceived usefulness and perceived ease of use—shape attitudes, behavioural intentions, and ultimately actual use, and the model remains popular for its parsimony and predictive power (Kemp et al., 2019). TAM has been applied widely in education, from measuring acceptance of AI-based assessment (Sánchez-Prieto et al., 2019, 2020) to the adoption of conferencing and learning platforms (Alfadda & Mahdi, 2021; Al-Adwan et al., 2023). A consistent lesson from this body of work is that the two core beliefs are themselves shaped by external variables, so studies



increasingly extend TAM with additional antecedents rather than treating it as a closed model.

Instructor adoption of AI and its determinants

Studies of teachers specifically point to a cluster of determinants behind these core beliefs. Self-efficacy, personal innovativeness, and perceived risk emerge as key drivers of perceived usefulness and ease of use (Al-Adwan et al., 2023), and computer self-efficacy correlates positively with attitudes, intentions, and actual use (Alfadda & Mahdi, 2021). Work using SEM with teacher samples likewise finds that perceived ease of use and usefulness—mediated by subjective norms, innovativeness, training, and facilitation—govern acceptance (Rafikasari & Iriawan, 2021). Comparative and review work adds that adoption is also shaped by interest, by perceived stress or pressure, and by the availability of training and support (Adiguzel et al., 2023; Bergdahl & Sjöberg, 2025; Chounta et al., 2022; Park, 2021; Wu, 2022), and that willingness to adopt varies by discipline (Ma & Lei, 2024). These findings motivate extending TAM with self-efficacy, interest, stress, and training.

TAM is adopted here for three reasons. First, it directly models the perceptions this study seeks to measure—usefulness, ease of use, attitude, and use. Second, it is well validated in educational and AI-acceptance contexts (Kemp et al., 2019; Sánchez-Prieto et al., 2020). Third, its openness to external variables permits the inclusion of self-efficacy, interest, stress, and training, which the literature identifies as salient for instructors and which are particularly relevant to a tool-oriented discipline such as product design.

Research Hypotheses

H1. Product design instructors at Shandong universities hold both positive and negative perceptions of using AI in teaching product design courses.

H2. Self-efficacy, interest, and stress are positively associated with instructors' perceived usefulness and perceived ease of use of AI.



H3. Training is an effective means of promoting instructors' intention to use AI in teaching product design at Shandong universities.

Drawing on the reviewed literature, the study proposes the conceptual framework shown in Figure 1. Self-efficacy, interest, and stress act as antecedents of perceived usefulness and perceived ease of use; these in turn shape attitudes toward use, which—together with training—influence actual use of AI in teaching.

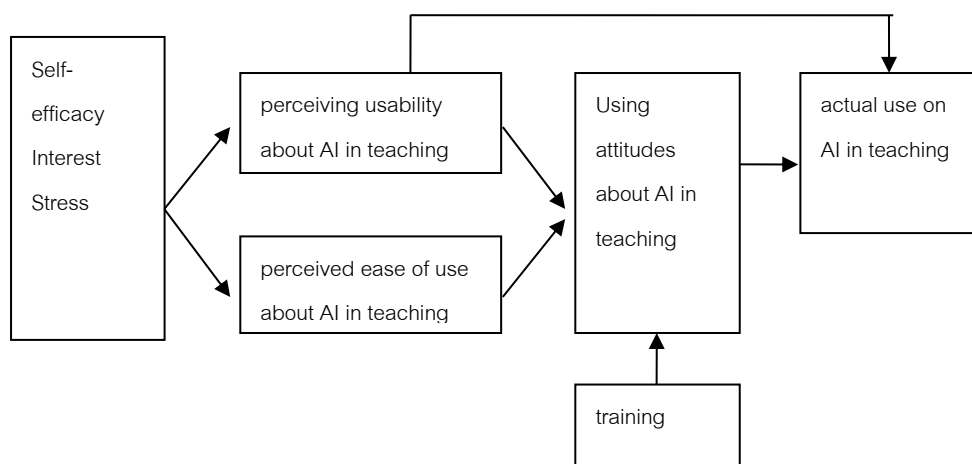


Figure 1. Conceptual framework based on the Technology Acceptance Model (TAM).

Methodology

Research design

This study employed a mixed-methods design that combined a quantitative survey with qualitative interviews to address the research objectives. The quantitative strand tested the hypothesised relationships among the TAM constructs using structural equation modelling (SEM), while the qualitative strand explored instructors' perceptions in greater depth; integrating the two strands allowed the interview findings to help explain and contextualise the statistical results.

Population, sampling, and participants

The target population comprised instructors teaching product design at universities in Shandong Province, China. In total, the population comprised approximately 235 instructors across 11 universities, identified from the provincial higher-



education teaching directory. Because this population is limited, a census (comprehensive) sampling approach was used rather than probability sampling. A total of 208 instructors completed the questionnaire. In all, 235 questionnaires were distributed and 208 were returned and usable, a response rate of 88.5%. Participant demographics—gender, age, teaching experience, academic rank, and prior experience with AI tools—are summarised in Table 1. For the qualitative strand, 15 instructors were selected through purposive sampling. Interviewees were selected to vary in gender, academic rank, and teaching experience; saturation was judged to be reached when no new themes emerged in the final three interviews.

Instruments and measures

Data were collected with a structured questionnaire operationalising the framework's constructs: self-efficacy, interest, stress, training, perceived usefulness, perceived ease of use, attitude toward use, and actual use. Each construct was measured with three to five items on a five-point Likert scale (1 = strongly disagree to 5 = strongly agree); items were adapted from Davis (1989) and subsequent TAM studies and reworded for the product-design context. All constructs exceeded the .70 threshold for Cronbach's alpha (Table 2). Confirmatory factor analysis yielded standardised loadings from .61 to .84, with composite reliability and average variance extracted exceeding .70 and .50 respectively (Table 2); the KMO measure was .91 and Bartlett's test of sphericity was significant ($p < .001$). The qualitative strand used a semi-structured interview protocol. The protocol comprised eight open-ended questions and was expert-reviewed and pilot-tested with two instructors before use.

Data collection

Data were collected between March and May 2024 through an online questionnaire; participants were invited by email and gave informed consent electronically before responding.



Data analysis

Quantitative data were analysed in AMOS. Descriptive statistics summarised the sample and constructs; a measurement model was assessed via CFA; and the structural model was estimated to test H1–H3. Model fit was evaluated against χ^2/df , CFI, TLI, RMSEA, and SRMR (Table 3), and the standardised path coefficients are reported in Table 4. Qualitative interview data were transcribed and analysed thematically in NVivo. Coding combined deductive codes from the TAM constructs with inductive codes for emergent themes; two researchers coded independently, achieving Cohen’s $K = .82$.

Results

Results are presented in three parts: quantitative findings from the SEM analysis, qualitative findings from the thematic analysis, and an integration of the two.

Quantitative findings

Table 1 summarises the characteristics of the 208 respondents. Table 2 reports the reliability and convergent validity of the measurement model. Table 3 reports the model-fit indices, and Table 4 reports the standardised path coefficients used to test the hypotheses.

Table 1. Characteristics of respondents ($N = 208$).

Variable	Category	n	%
Gender	Male	96	46.2
	Female	112	53.8
Age	< 30	41	19.7
	30–39	88	42.3
	40–49	57	27.4
	≥ 50	22	10.6
Teaching experience	< 5 years	58	27.9
	5–10 years	79	38.0
	> 10 years	71	34.1



Variable	Category	n	%
Academic rank	Teaching assistant	34	16.3
	Lecturer	98	47.1
	Associate professor	56	26.9
	Professor	20	9.6
Prior AI use	Yes	149	71.6
	No	59	28.4

Table 2. Reliability and convergent validity of the measurement model.

Construct	Items	Cronbach's α	CR	AVE
Self-efficacy	5	.88	.89	.62
Interest	4	.85	.86	.61
Stress	5	.83	.84	.57
Training	4	.87	.88	.65
Perceived usefulness	5	.90	.91	.67
Perceived ease of use	5	.89	.90	.64
Attitude toward use	4	.86	.87	.63
Actual use	3	.82	.83	.62

Table 3. Structural model fit indices.

Fit index	Recommended threshold	Obtained value
χ^2/df	< 3.0	1.82
CFI	> .90	.95
TLI	> .90	.94
RMSEA	< .08	.063
SRMR	< .08	.051



Table 4. Standardised path coefficients for the hypothesised relationships.

Path	Std. β	C.R.	p	Result
Self-efficacy $\rightarrow$ Perceived usefulness	.28	4.12	< .001	Supported
Self-efficacy $\rightarrow$ Perceived ease of use	.31	4.45	< .001	Supported
Interest $\rightarrow$ Perceived usefulness	.19	3.05	.002	Supported
Interest $\rightarrow$ Perceived ease of use	.22	3.38	< .001	Supported
Stress $\rightarrow$ Perceived usefulness	.36	5.02	< .001	Supported
Stress $\rightarrow$ Perceived ease of use	.33	4.77	< .001	Supported
Training $\rightarrow$ Attitude toward use	.27	3.96	< .001	Supported
Perceived usefulness $\rightarrow$ Attitude	.41	5.83	< .001	Supported
Perceived ease of use $\rightarrow$ Attitude	.24	3.52	< .001	Supported
Attitude $\rightarrow$ Actual use	.58	7.21	< .001	Supported

The structural model supported the hypotheses. Self-efficacy, interest, and stress were each positively and significantly associated with perceived usefulness and perceived ease of use ($\beta = .19$ to $.36$, all $p < .01$). Among the three, stress was the strongest predictor, followed by self-efficacy and then interest (stress $\beta = .33$ – $.36$; self-efficacy $\beta = .28$ – $.31$; interest $\beta = .19$ – $.22$). Training was positively associated with attitude toward use ($\beta = .27$, $p < .001$). In turn, perceived usefulness and perceived ease of use predicted attitude, and attitude predicted actual use (perceived usefulness $\rightarrow$ attitude $\beta = .41$; perceived ease of use $\rightarrow$ attitude $\beta = .24$; attitude $\rightarrow$ actual use $\beta = .58$; all $p < .001$;



$R^2 = .42, .39, .51$, and $.34$ for perceived usefulness, perceived ease of use, attitude, and actual use respectively).

Discussion

Hypothesis 1: positive and negative perceptions

Consistent with H1, instructors expressed both positive and negative perceptions. On the positive side, AI was seen as an enabling tool that improves efficiency and frees teaching time for creative guidance; instructors noted that AI tools can simulate corporate workflows, narrowing the gap between university teaching and industry needs, and that learning-analytics systems can identify weaknesses in students' design thinking and provide targeted support. On the negative side, instructors voiced concern that AI may threaten the essence of design education—diminishing creativity and homogenising student work, as in the stylistic convergence associated with generative image tools—and that experienced teachers face pressure to move from “skills imparter” to “AI-collaborative coach” (Chounta et al., 2022).

Hypothesis 2: self-efficacy, interest, and stress

Supporting H2, instructors with higher self-efficacy were more likely to view AI tools as learnable and masterable, experienced less anxiety toward new technologies, and were more motivated to experiment so they more readily perceived AI as easy to use and useful, and were more proactive in exploring its applications in instructional design, creative-process optimisation, personalised tutoring, and trend analysis (Bergdahl & Sjöberg, 2025).

Interest functioned as a second positive driver. Instructors with a strong interest in AI invested more time in learning the tools, lowered their own learning barriers, and engaged in deeper cognitive processing continuing to follow AI developments and to consider how to integrate AI into teaching and design workflows which helped them discover AI's distinctive value and form a fuller understanding of its usefulness (Park, 2021).

Stress, finally, operated as “challenging pressure.” Recognising that AI is a future trend and that mastery is necessary to remain competitive heightened instructors'



vigilance and learning motivation, prompting them to attend more closely to AI's functions and to seek resources and solutions; once initial obstacles were overcome, the resulting efficiency or pedagogical gains strengthened their positive perceptions (Wu, 2022). These factors do not act in isolation: high self-efficacy and strong interest can buffer the negative effects of stress and even convert it into motivation, while successfully coping with challenge can in turn raise self-efficacy.

Hypothesis 3: training

Supporting H3, training emerged as an effective lever for promoting practical use. Through practical exercises, case teaching, and workshops, training can improve instructors' ability to operate AI tools, solve technical problems, and integrate AI into specific teaching designs such as project tasks and assessment criteria (Vlasova et al., 2019). Universities in Shandong can build on this by offering differentiated training, establishing an instructor AI-innovation network (for example, in cooperation with the Shandong Industrial Design Association), holding teaching-case competitions, introducing an "AI-capability micro-certification" system, and recognising teaching innovation through awards (Lee et al., 2024).

Discipline-specific findings in product design

A distinctive contribution of this study is its disciplinary lens. Compared with faculty in more theoretical or traditional craft fields, product design instructors showed notably higher acceptance of, and willingness to adopt, AI (Ma & Lei, 2024). This openness reflects the discipline's character. Product design has always been tool-dependent from hand-drawing and model-making to CAD, 3D printing, and rendering—so its instructors are accustomed to learning new tools and treat AI as another such tool (Dekkers et al., 2013). The field's innovation- and problem-solving orientation leads instructors to view AI as a catalyst rather than a threat, and its interdisciplinary nature spanning engineering, materials, aesthetics, human-computer interaction, marketing, and psychology makes them more receptive to a technology rooted in computer science (Zheng et al., 2021).

This natural openness provides fertile ground for the mechanisms in H2 and H3: where instructors are already inclined toward new tools, building skills (training), confidence (self-efficacy), and interest, and managing stress, are more likely to convert willingness into actual use. The discipline's "tool affinity" thus makes product design



both an ideal site for integrating AI into education and a useful comparison point for understanding how technology-adoption behaviour differs across fields.

Conclusion

This study examined product design instructors' perceptions of AI in teaching at universities in Shandong Province through the lens of an extended TAM. Instructors were generally positive toward AI; self-efficacy, interest, and stress were positively associated with perceived usefulness and ease of use with stress the strongest predictor and training was positively associated with attitudes toward use. The qualitative findings reinforced these patterns and highlighted the discipline's tool-oriented, interdisciplinary character as a facilitator of adoption.

Limitations

Several limitations should be noted. The study was confined to product design instructors in a single province, which limits generalisability; the cross-sectional design precludes causal inference; and self-report measures may be subject to social-desirability bias. With 208 of approximately 235 instructors responding (88.5%), the realised sample appears broadly representative of the target population, though the single-province scope still limits wider generalisation.

Recommendations

Universities are encouraged to strengthen discipline-specific AI training and capacity building for product design instructors through workshops, case-based teaching, and practical exercises to lower teaching costs and improve effective classroom use. Establishing an instructor AI-innovation network, offering micro-credentials, and recognising teaching innovation may further support the transition from willingness to actual use (Lee et al., 2024). Future research could extend the model to other disciplines and regions and adopt longitudinal designs to trace adoption over time.



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