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Measuring the Acceptance of AI-Assisted Design: Developing the AI-Assisted Design Acceptance Inventory through its Relationship with Technology Anxiety, Creative Self-Efficacy, and Aesthetic Sensitivity

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Abstract

Background and Research Gap: With the rapid proliferation of generative artificial intelligence (AI) in the field of design, designers are experiencing profound transformations in workflows and creative processes. From conceptual ideation to the generation of final prototypes, AI technologies are reshaping the entire design ecosystem. However, existing design research often overlooks the significant impact of individual differences among designers on the acceptance and effectiveness of AI tools. Although the technology itself continues to advance, its potential may remain underutilized without active user adoption. Both academia and industry currently lack standardized instruments to measure AI tool acceptance specifically in design contexts, limiting our understanding of the underlying mechanisms of human–AI co–creation.

Methods: This study systematically defines and operationalizes the core construct of AI-Assisted Design Acceptance (AI-ADA) and develops the AI-Assisted Design Acceptance Inventory (AI-ADAI). A rigorous survey was conducted with a large sample of design students and professionals (N = 494). Exploratory factor analysis (EFA) and comprehensive statistical tests were employed to evaluate the reliability and validity of the inventory.

Practical Approach: To examine the external validity and theoretical significance of the scale, multiple linear regression models were employed, incorporating three

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well-established psychological constructs: technology anxiety, creative self-efficacy, and aesthetic sensitivity. These analyses enabled in-depth cross-validation of the subdimensions of AI-ADAI and exploration of their underlying mechanisms.

Key Findings: Factor analysis revealed four latent dimensions of AI-ADAI: Human-AI Co-creation, Iterative Optimization, Ethical & Copyright Awareness, and Design Efficiency Enhancement. Regression results indicated that creative self-efficacy was positively associated with AI acceptance ($\beta = 0.256$, $p < 0.001$), whereas technology anxiety showed a significant negative relationship ($\beta = -0.109$, $p < 0.001$). Interestingly, aesthetic sensitivity did not exhibit a simple linear relationship with specific subdimensions (e.g., iterative optimization) but followed a complex nonlinear inverted-U pattern, providing new insights into experienced designers' resistance to adopting AI technologies.

Significance: This study introduces the first rigorously validated standardized instrument for quantitatively assessing designers' acceptance of AI tools. The findings enrich theoretical frameworks at the intersection of human-computer interaction and design, extend the applicability of traditional technology acceptance models, and offer targeted strategies for curriculum reform in design education and psychological interventions in organizational digital transformation.

Keywords: AI-assisted design; scale development; technology acceptance model; technology anxiety; creative self-efficacy; aesthetic sensitivity; human-AI co-creation

1. Introduction

In recent years, with the rapid advancements in deep learning and generative artificial intelligence (AI) technologies, tools such as Midjourney, Stable Diffusion, DALL-E, and ChatGPT have been integrated into the daily workflows of the design industry at an unprecedented pace and depth. These tools not only significantly enhance design productivity and shorten the cycle from conceptual ideation to visual realization but also fundamentally reshape designers' cognitive frameworks and creative paradigms. AI is evolving from a passive, instruction-driven "execution tool" into an autonomous and heuristic "collaborative co-creator." However, this technological shift presents both unprecedented challenges and opportunities for the designer community. In practical applications, designers' responses to AI tools exhibit substantial individual differences: some quickly adapt their mindset, actively integrating AI to expand their creative boundaries and even regarding it as an indispensable source of inspiration, while others demonstrate resistance, experience

cognitive friction during use, or develop profound anxiety about their professional future.

Despite the growing body of research at the intersection of design and AI, the majority of studies focus primarily on improving algorithmic performance, evaluating the quality of generated outputs, or automating specific design tasks such as layout and color schemes. These studies often prioritize technology over the designer, largely overlooking the complex psychological mechanisms and deep-seated attitudinal tendencies that emerge when designers confront technological change. On the other hand, existing technology acceptance models (e.g., the classical Technology Acceptance Model [TAM] and its extensions such as UTAUT) were developed for general information systems or everyday office software. Their core evaluation metrics, typically limited to “perceived usefulness” and “perceived ease of use,” are insufficient for capturing the inherent complexity, ambiguity, and high creativity demands characteristic of design activities. Design is not merely a linear problem-solving process; it is a creative endeavor involving exploration, meaning-making, emotional expression, and aesthetic communication. Therefore, assessing designers’ acceptance of AI tools requires a standardized measurement instrument tailored to the design context—one that reflects the cognitive and attitudinal traits inherent in design thinking.

Against this backdrop, the present study focuses on the following core questions: How can designers’ acceptance of AI-assisted design be measured scientifically, systematically, and multidimensionally? What underlying psychological and attitudinal factors constitute this acceptance? To address these questions, we developed and rigorously validated the AI-Assisted Design Acceptance Inventory (AI-ADAI). Conceptually, we delineated the boundaries and theoretical underpinnings of AI-ADA, while empirically exploring its latent factor structure using large-scale survey data. Furthermore, to assess the theoretical validity and predictive capability of the newly developed instrument, we incorporated three psychological constructs closely related to design practice and technology adoption: technology anxiety (reflecting negative emotions toward technology), creative self-efficacy (reflecting confidence in one’s creative abilities), and aesthetic sensitivity (reflecting a designer’s core professional competencies).

The objective of this study is explicit: to fill the gap in standardized measurement tools at the intersection of design psychology and human-AI collaboration. In designing the AI-ADAI, we deliberately excluded superficial evaluations of proficiency in specific AI software (e.g., Photoshop AI or Midjourney) and instead focused on deeper, more generalizable constructs such as beliefs, attitudinal tendencies, and cognitive patterns. The structure of this paper is as follows: Section 2 provides a systematic review of AI applications in design and the literature on technology

acceptance, establishing the theoretical foundation for the core construct. Section 3 details the methodology for scale development, including item generation and rigorous data collection procedures. Section 4 presents data processing steps, exploratory factor analysis, and regression modeling results. Section 5 offers an in-depth discussion of the findings, with a particular focus on mechanisms underlying nonlinear relationships. Finally, Sections 6 and 7 summarize key conclusions and discuss the theoretical contributions and practical implications for design practice.

2. Related Work

This section reviews the current applications of artificial intelligence (AI) in the design domain, discusses the limitations of existing technology acceptance measurement tools in design-specific contexts, and establishes the theoretical rationale for incorporating three cross-disciplinary psychological constructs: technology anxiety, creative self-efficacy, and aesthetic sensitivity.

2.1. AI-Assisted Design and Technology Acceptance

AI has been widely applied in various stages of design, including conceptual ideation, parametric modeling, layout optimization, and user experience testing [1]. However, the highly nonlinear and subjective nature of design processes renders the integration of AI tools more complex than mere efficiency gains or cost reduction. Prior studies highlight a “control paradox” in human-AI collaboration within design: designers seek unexpected inspiration from AI while simultaneously fearing a loss of control over final outcomes [2].

Although the Technology Acceptance Model (TAM) and its extensions, such as the Unified Theory of Acceptance and Use of Technology (UTAUT), have been extensively studied [3], these models primarily focus on perceived usefulness and perceived ease of use, making them more suitable for enterprise resource planning (ERP) systems or routine office software [4]. In innovation-driven and emotionally expressive domains such as design, traditional models fail to capture the complex attitudes designers hold toward AI as a “collaborative co-creator” [5]. For example, a designer may recognize an AI tool as highly user-friendly and capable of rapidly generating outputs yet still resist using it in core creative tasks. This highlights the need for a measurement instrument specifically designed to account for characteristics of design thinking in evaluating AI acceptance.

2.2. Cross-Disciplinary Psychological Constructs

To achieve a more nuanced understanding of AI-assisted design acceptance, this study incorporates three key psychological traits drawn from psychology and human-computer interaction to form a multidimensional theoretical framework.

1. **Creative Self-Efficacy:** Creative self-efficacy, derived from Bandura's social cognitive theory, refers to one's belief in their ability to produce innovative outcomes [8]. Designers with high creative self-efficacy are more willing to take risks, explore uncharted territories, and demonstrate resilience when facing complex challenges [9]. When interacting with AI tools, these designers are more likely to perceive AI as a scaffold that extends their creative capabilities rather than as a threat [10]. They are confident in integrating AI-generated outputs into their own design frameworks. Thus, creative self-efficacy is hypothesized as a key driver of deep engagement with AI tools;
2. **Aesthetic Sensitivity:** Aesthetic sensitivity is a core professional attribute of designers, reflecting the ability to perceive and evaluate form, proportion, color, and visual harmony in stimuli [11]. With the advent of AI-generated high-quality imagery, the competitive advantage in design is shifting from manual execution skills toward aesthetic judgment and curatorial abilities. Designers with high aesthetic sensitivity may critique AI-generated outputs for being "generic" or lacking distinctiveness, yet they may also excel at guiding AI to produce aesthetically valuable results through precise prompts [12]. Consequently, the relationship between aesthetic sensitivity and AI acceptance may not be linear, presenting a valuable avenue for exploration;
3. By integrating these cross-disciplinary perspectives, this study aims not only to develop a reliable measurement instrument but also to uncover the deep psychological mechanisms that influence designers' adoption of AI. The findings are expected to provide a theoretical foundation for design education and professional practice in the context of AI-assisted creativity.

3. Methodology

This study followed a standard psychometric scale development process to ensure the reliability and validity of the AI-Assisted Design Acceptance Inventory (AI-ADAI). The overall research strategy adopted a "theory-driven model construction followed by empirical validation and refinement with large-scale data" approach.

3.1. Research Strategy and Scale Operationalization

The development of AI-ADAI proceeded in three sequential stages: item generation, expert content validity assessment, and large-scale empirical testing (see Figure 1)).

First, based on a comprehensive literature review and in-depth interviews with 15 experienced designers, we identified core behavioral patterns and attitudinal

tendencies exhibited by designers when using AI tools. Drawing on existing informed design strategy matrices, we operationalized AI acceptance across key design stages—such as problem understanding, idea generation, and iterative refinement—into specific attitudinal statements. The initial item pool (proto-items) comprised 32 statements, measured on a 7-point Likert scale (1 = strongly disagree, 7 = strongly agree). To mitigate response bias, several items were reverse-coded.



Figure 1. AI-ADAI Development and Validation Workflow.

3.2. Data Collection Procedure

Quantitative survey data from a large and representative sample were collected to empirically validate the scale. Strict sampling strategies and quality control measures were applied to ensure data integrity.

1. Sample Selection and Recruitment

The target population was strictly defined as individuals currently engaged in design education or design-related professional work, ensuring that respondents possessed the necessary expertise to evaluate AI-assisted design tools. Recruitment channels included:

- Design schools at multiple renowned domestic universities (e.g., majors in Visual Communication, Industrial Design, Architecture);
- Professional online design communities and forums (e.g., ZCOOL, Behance China);
- In-house design teams at technology companies and design agencies.

Prior to survey administration, participants were informed of the study’s purpose and assured of data anonymity and exclusive academic use.

2. Questionnaire Structure and Measurement Instruments;

The questionnaire consisted of five main sections, designed to comprehensively capture respondents’ attitudes and relevant psychological traits. All core constructs were measured using established 7-point Likert scales (1 = strongly disagree, 7 = strongly agree). Table 1 summarizes the structure of the questionnaire and the measurement instruments employed.

Table 1. Overview of Questionnaire Structure and Measurement Instruments.

Section Measured Construct / Number of Source / Reference	Example Item
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	Content	Items		
1	Demographic Information	6	Self-developed	“How many years have you been working in the design field?” “On average, how many hours per week do you use AI design tools?”
2	AI-Assisted Design Acceptance (AI-ADAI)	32 (initial)	Developed in this study	“I believe AI can help me overcome the limitations of my current design thinking.”
3	Technology Anxiety	6	Adapted from Meuter et al., 2003 [6]	“When faced with rapidly evolving AI design software, I often feel overwhelmed.”
4	Creative Self-Efficacy	3	Tierney & Farmer, 2002 [8]	“I am confident in my ability to produce novel and valuable design solutions.”
5	Aesthetic Sensitivity	8	Blijlevens et al., 2017 [11]	“I can easily detect subtle differences in composition and color balance between two visually similar images.”

Prior to the formal survey administration, a pilot study was conducted with five design faculty members and five senior UI/UX designers. Based on their feedback, several items were refined to ensure clarity and alignment with the Chinese design context. For example, the generic term “Technology” in the original English scale was specified as “AI generation tools (e.g., Midjourney, Stable Diffusion)” to reflect the actual usage and understanding of designers in practice.

3. Data Quality Control.

To prevent invalid responses from affecting subsequent factor analyses, several quality control mechanisms were embedded in the online survey platform (Qualtrics):

- Response time threshold: The system automatically recorded completion times, and surveys completed in less than 120 seconds—determined from the pilot study as the minimum reasonable duration—were excluded;
- Attention check items: One attention check item was randomly inserted in both Part 3 and Part 5 of the survey (e.g., “To confirm that you are reading carefully, please select ‘Somewhat Agree’ for this item”). Surveys that failed to meet the requirement were automatically discarded;
- Reverse-coded items: Five reverse-coded items were included in the initial AI-ADAI item pool (e.g., “I believe that over-reliance on AI may weaken my core competencies”) to identify and remove patterned responses, such as selecting the same option throughout or exhibiting a “Z-shaped” response trajectory.

3.3. Data Analysis Procedures

Data processing and analysis were conducted using SPSS 26.0 and Python’s Statsmodels library. The analytical workflow followed a rigorous four-step procedure:

1. Data cleaning and missing value imputation: After removing invalid responses, missing values caused by system errors (<1.5% of the total data) were imputed using multiple imputation to ensure dataset completeness;
2. Assessment of normality and multicollinearity: Prior to factor and regression analyses, skewness and kurtosis of all continuous variables were examined, with absolute values below 2 to meet the normality assumption. Variance inflation factors (VIFs) were also computed, all below 3, indicating no serious multicollinearity;
3. Exploratory Factor Analysis (EFA): Principal Component Analysis (PCA) with Varimax orthogonal rotation was employed to extract latent factors. Factor retention criteria included: (a) eigenvalues greater than 1, (b) positions above the scree plot inflection point, and (c) each factor contributing at least 5% of variance. Item retention required loadings greater than 0.5 on the primary factor and cross-loadings below 0.3 on other factors;
4. Multiple linear regression and moderation analysis: To test theoretical hypotheses, multiple stepwise regression models were constructed using the AI-ADAI total score and its four subdimensions as dependent variables, and technology anxiety[7], creative self-efficacy, and aesthetic sensitivity as independent variables. To examine potential nonlinear effects of aesthetic sensitivity, a quadratic term was added to the models.

4. Data and Results

A total of 512 initial responses were collected over a three-week online survey period. Following the rigorous data cleaning procedures described above—which excluded 8 responses completed in less than 120 seconds, 6 responses failing the attention check items, and 4 responses exhibiting patterned response behavior—494 high-quality valid responses were retained for subsequent statistical analyses. The effective response rate reached 96.5%, and the sample size greatly exceeded the minimum requirement for exploratory factor analysis (EFA), which is typically recommended as 5–10 times the number of items; in this study, the sample was 15.4 times the initial item pool.

4.1. Sample Descriptive Statistics and Overview of Key Variables

Detailed demographic characteristics of the valid sample are summarized in Table 2. Participants ranged in age from 18 to 55 years, with a mean age of 26.5 years (SD = 4.2, see Figure 2), reflecting a relatively young profile consistent with the current design industry and early adopters of AI technologies. In terms of gender distribution, females slightly outnumbered males, accounting for 53.0% and 45.0%,

respectively. The average design experience of respondents was 3.5 years (SD = 3.1), spanning from current students to senior design directors with over 10 years of experience.

Table 2. Demographic Characteristics of Valid Sample (N = 494).

Demographic Variable	Category	Frequency (n)	Percentage (%)
Gender	Male	222	45.0
	Female	262	53.0
	Other / Prefer not to say	10	2.0
Age (years)	18–24	198	40.1
	25–30	212	42.9
	31–40	69	14.0
	41+	15	3.0
Years of Professional Experience	0–2 (including students)	237	48.0
	3–5	148	30.0
	6–10	84	17.0
	>10	25	5.0
Professional Background	Visual / Graphic Design	173	35.0
	Interaction / UI/UX Design	138	28.0
	Industrial / Product Design	89	18.0
	Architecture / Interior Design	59	12.0
	Other Design Fields	35	7.0

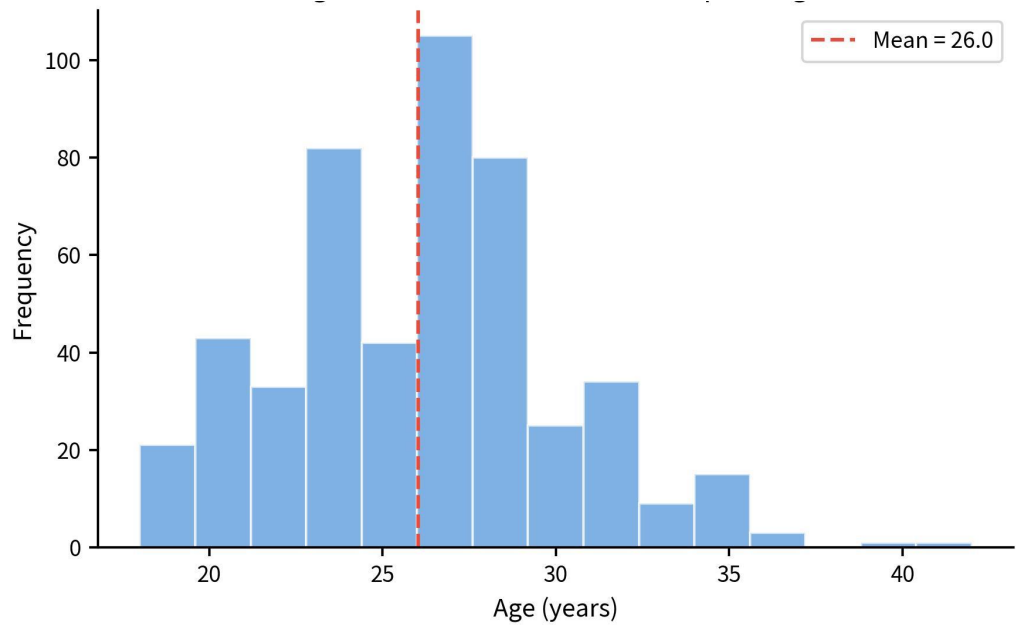


Figure 2. Distribution of Participant Age.

Regarding professional background, Visual Communication and Graphic Design were the most represented disciplines (35%), followed by Interaction and UI/UX Design (28%). This distribution reflects the current penetration of generative AI tools, such as image generation models, in these specific design domains (see Figure 3).

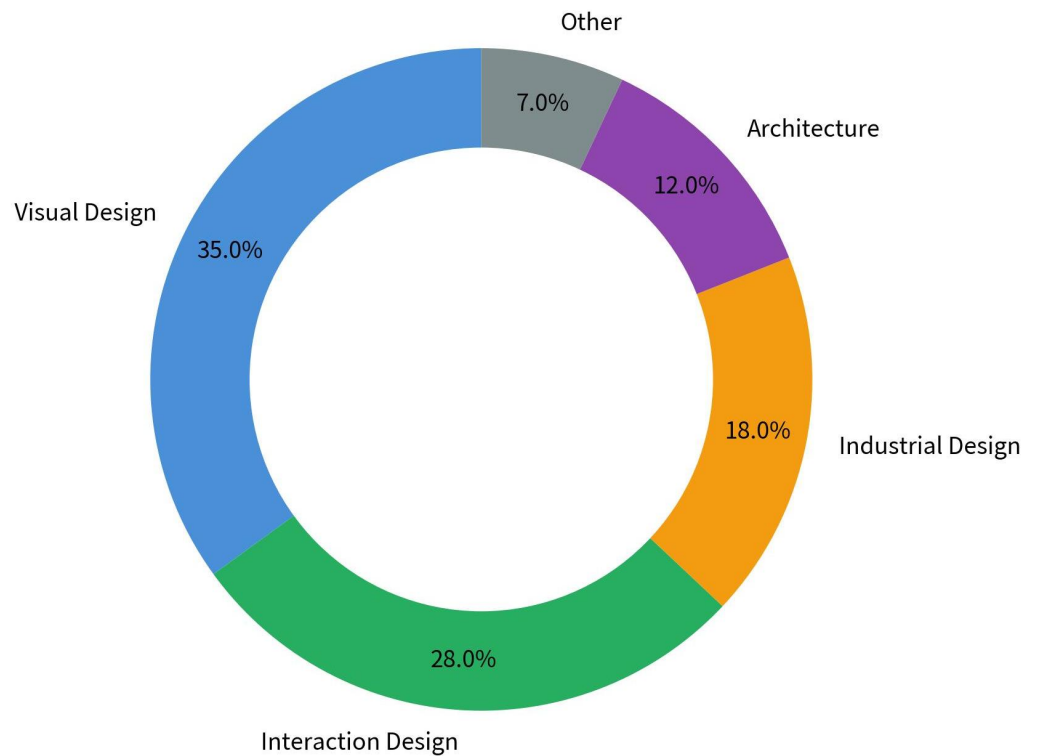


Figure 3. Distribution of Participant Design Backgrounds.

The score distributions of the four core continuous variables are summarized in Table 3. Respondents' creative self-efficacy ($M = 5.40$, $SD = 1.10$) and aesthetic sensitivity ($M = 5.60$, $SD = 0.90$) were generally at moderately high levels, reflecting a strong sense of professional confidence among the design population. In contrast, technology anxiety ($M = 3.41$, $SD = 1.27$) exhibited substantial individual variability, indicating that not all designers experience apprehension toward AI. The overall AI-assisted design acceptance score averaged 4.71 ($SD = 0.47$), suggesting an overall positive but cautious attitude toward adopting AI tools in design practice.

Table 3. Descriptive Statistics of Core Continuous Variables.

Variable	Minimum	Maximum	Mean (M)	Standard Deviation (SD)	Skewness	Kurtosis
Technology Anxiety (TA)	1.03	6.87	3.41	1.27	0.42	-0.31
Creative Self-Efficacy (CSE)	2.15	7.00	5.40	1.10	-0.58	0.12
Aesthetic Sensitivity (AS)	2.80	7.00	5.60	0.90	-0.65	0.28
AI-Assisted Design Acceptance (AI-ADAI, Total)	3.08	6.06	4.71	0.47	0.03	2.84

Regarding the scores of key variables, no significant differences were observed in overall AI-assisted design acceptance between genders (see Figure 4). However, a fluctuating trend in AI acceptance was observed with increasing years of professional experience, suggesting that designers' attitudes toward AI tools vary at different career stages (see Figure 5).

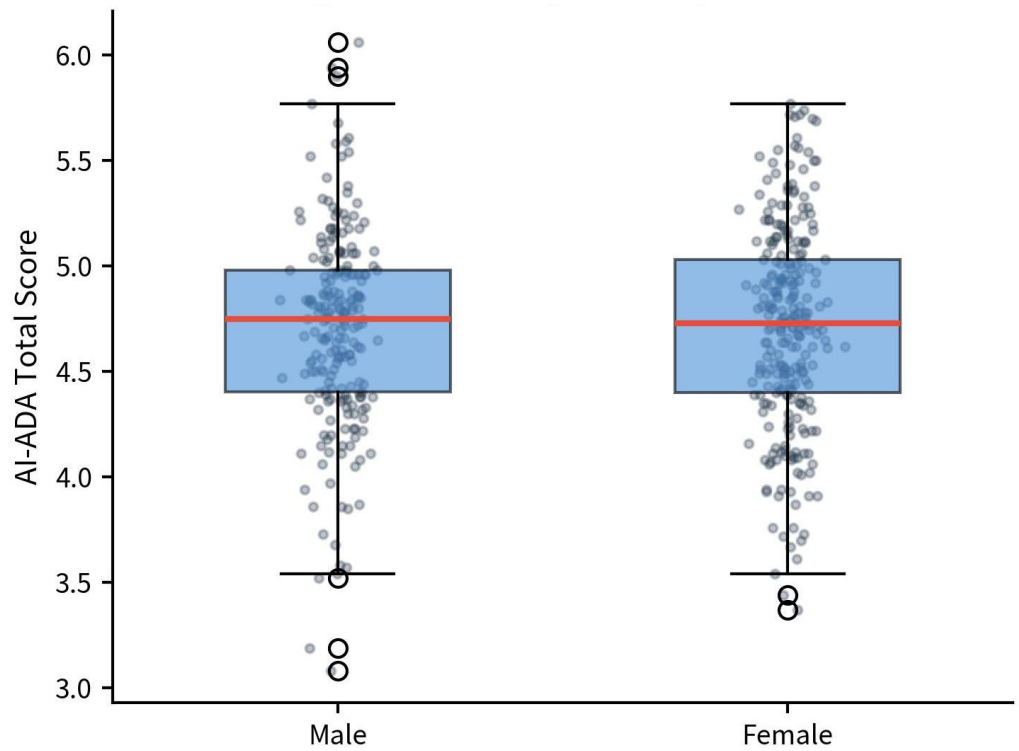


Figure 4. AI Acceptance by Gender.

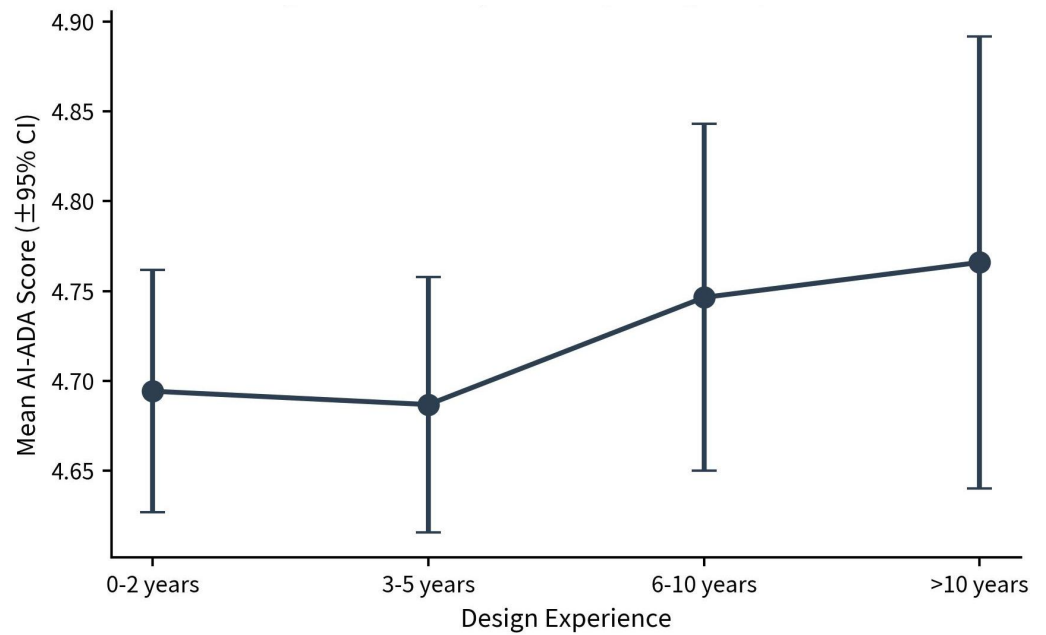


Figure 5. AI Acceptance by Design Experience.

4.2. Exploratory Factor Analysis (EFA)

Prior to conducting EFA, the suitability of the data for factor analysis was evaluated using the Kaiser–Meyer–Olkin (KMO) measure and Bartlett’s test of sphericity. The KMO value was 0.892, exceeding the recommended threshold of 0.8, and Bartlett’s test yielded a chi-square value of 6241.5 (df = 120, $p < 0.001$),

indicating significant correlations among variables and confirming that the dataset was highly suitable for factor extraction.

The results of the EFA strongly supported the hypothesized multidimensional structure of the scale. Using principal component analysis (PCA) with Varimax orthogonal rotation, four factors with eigenvalues greater than 1 were extracted (see Figure 6, scree plot). These four factors collectively explained 68.4% of the total variance, surpassing the commonly accepted threshold of 60%, providing strong evidence for the construct validity of the AI-ADAI scale.

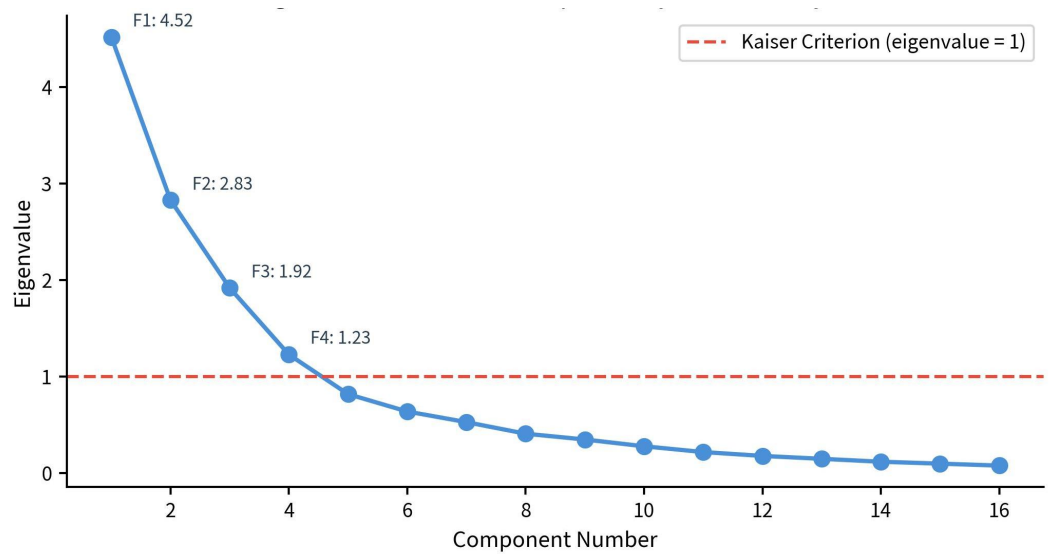


Figure 6. Scree Plot of Exploratory Factor Analysis.

After carefully examining the rotated factor loading matrix, six items with loadings below 0.5 or exhibiting substantial cross-loadings were removed. The final scale retained 16 items, with each factor comprising four items. Table 4 presents the factor names, representative items, and their respective factor loadings in detail.

Table 4. Results of Exploratory Factor Analysis for the AI-ADAI Scale (N = 494).

Factor & Variance Explained	Item ID	Item Description	Factor Loading	Cronbach's α
Factor 1: Human-AI Co-creation Explained variance: 22.5%	Q1	AI provides me with unexpected design inspirations.	0.812	0.86
	Q2	I am willing to use AI-generated sketches as a starting point for my creative work.	0.785	
	Q3	I regard AI as a "collaborative partner" that I can interact with.	0.763	
	Q4	I proactively seek AI assistance when encountering creative blocks.	0.741	
Factor 2: Iterative Optimization	Q5	I guide AI to improve outputs by modifying	0.805	0.84

Explained variance: 18.3%				
			prompts.	
	Q6	I frequently use AI to quickly generate multiple design variants for selection.	0.792	
	Q7	AI greatly accelerates my design prototype iteration process.	0.755	
	Q8	I enjoy working with AI iteratively to approach the ideal outcome.	0.728	
Factor 3: Ethical & Copyright Awareness				
Explained variance: 14.6%	Q9	I pay attention to copyright risks when using AI-generated materials.	0.821	0.81
	Q10	Designers should be responsible for the ethical implications of AI-generated works.	0.788	
	Q11	I feel uneasy when using unauthorized AI models.	0.746	
	Q12	I support explicitly indicating which parts of a project are AI-generated in commercial work.	0.712	
Factor 4: Design Efficiency Enhancement				
Explained variance: 13.0%	Q13	AI tools significantly reduce my time spent on repetitive tasks such as layout or cutouts.	0.835	0.83
	Q14	Mastering AI tools enables me to handle more design projects simultaneously.	0.801	
	Q15	AI tools lower the technical threshold for certain basic design tasks.	0.768	
	Q16	Using AI tools improves my overall work efficiency.	0.732	

Note: The Cronbach’s α for the overall AI-ADAI scale was 0.89, indicating excellent internal consistency reliability.

Figure 7 presents a violin plot visualizing the score distributions of the four subdimensions of the AI-ADAI scale. It can be observed that “Design Efficiency Enhancement” and “Iterative Optimization” exhibit generally high and concentrated scores, whereas “Ethical & Copyright Awareness” shows a relatively dispersed distribution, indicating greater variability in respondents’ perceptions in this dimension.

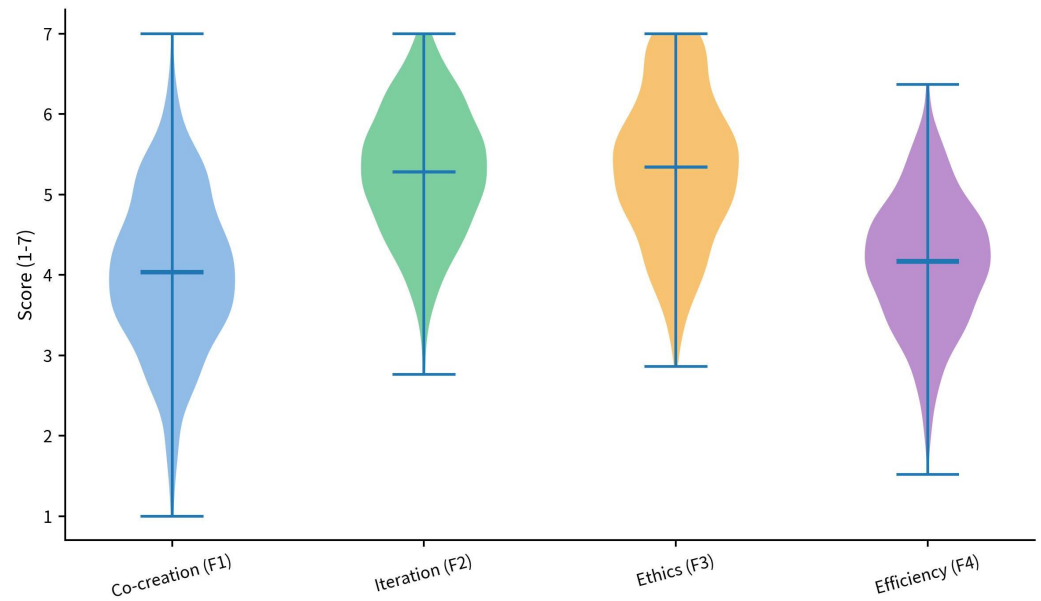


Figure 7. Score Distribution of AI-ADAI Subscales.

4.3. Correlation and Multiple Regression Analysis

To preliminarily explore the relationships among core variables, Pearson correlation analyses were conducted. The correlation heatmap (see Figure 8) shows that creative self-efficacy (CSE) was significantly positively correlated with overall AI-assisted design acceptance ($r = 0.55$, $p < 0.001$), whereas technology anxiety (TA) was significantly negatively correlated with overall AI acceptance ($r = -0.31$, $p < 0.001$). Aesthetic sensitivity (AS) exhibited a weak linear correlation with overall acceptance ($r = 0.12$, $p < 0.05$).

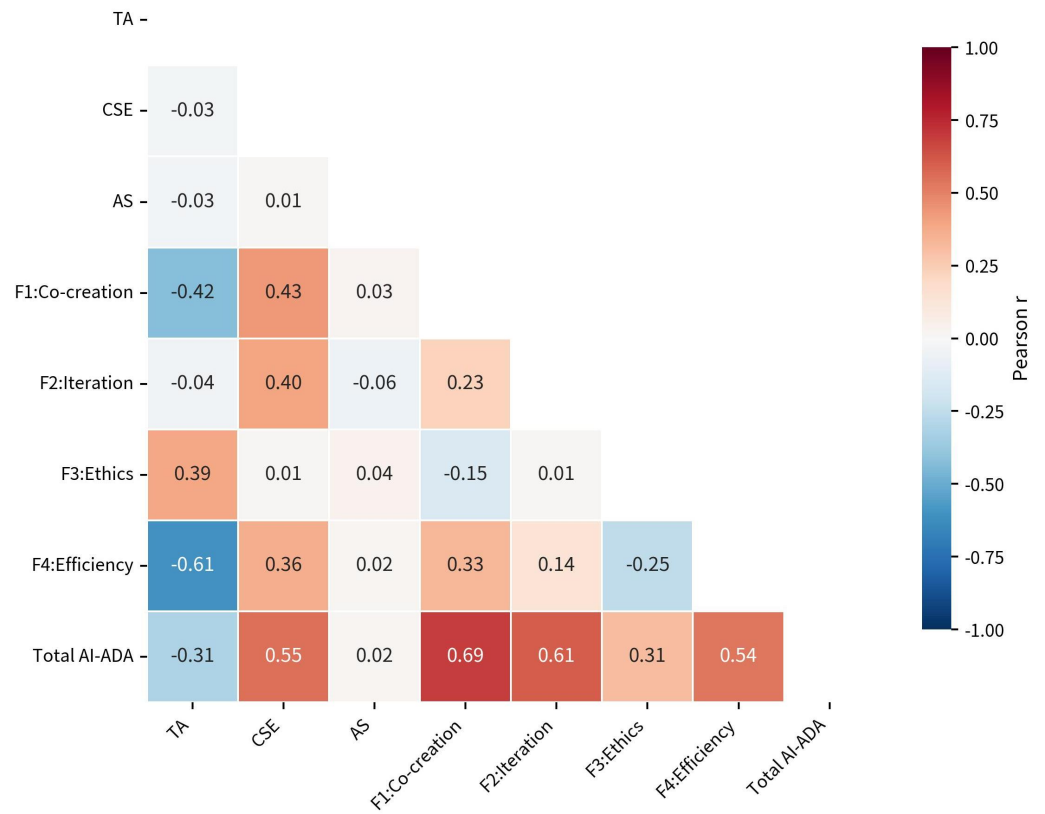


Figure 8. Pearson Correlation Heatmap of Core Variables.

To further test the theoretical hypotheses while controlling for potential confounding variables, a series of multiple linear regression models were constructed. The AI-ADA total score served as the dependent variable, with three psychological traits included as predictors after controlling for age, gender, and years of professional experience. The overall regression model was highly significant ($F(6, 487) = 54.2, p < 0.001$) and accounted for 39.3% of the total variance (Adjusted $R^2 = 0.385$). Model diagnostics (see Figure 9) indicated that the residuals were approximately normally distributed, with no evidence of heteroscedasticity, suggesting a good model fit.

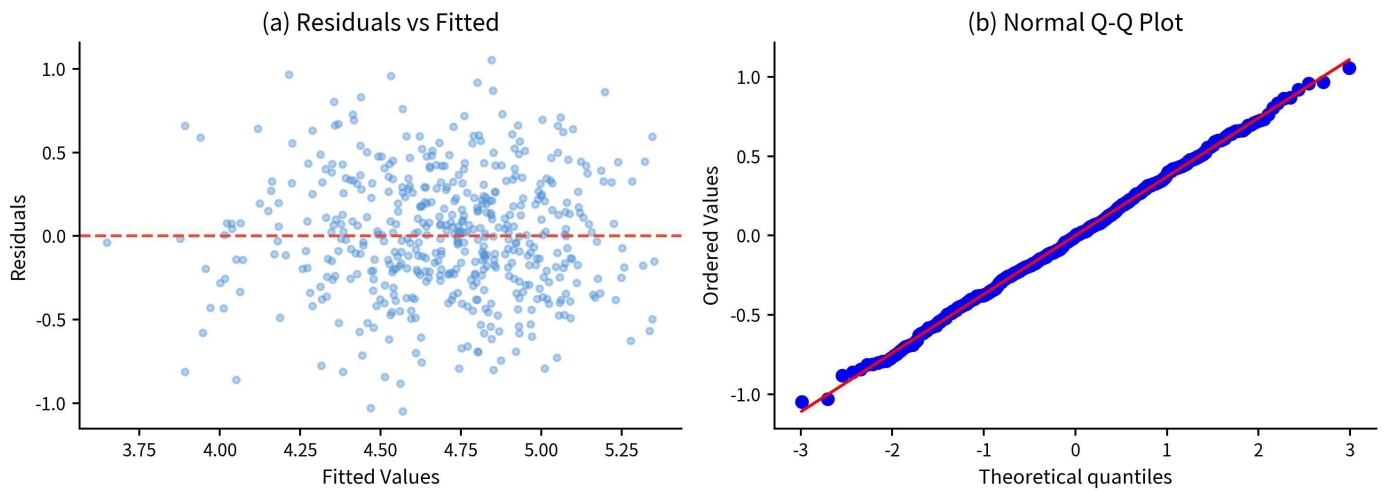


Figure 9. Regression Diagnostics.

The detailed results of the multiple regression analysis are presented in Table 5.

Table 5. Multiple Regression Models Predicting AI-Assisted Design Acceptance.

Predictor Variable	B (Unstandardized)	SE	β (Standardized)	t	p	VIF
Constant	2.145	0.286	—	7.50	<0.001	—
Control Variables						
Age	-0.012	0.008	-0.065	-1.50	0.134	1.45
Gender (Female = 1)	0.045	0.038	0.048	1.18	0.238	1.02
Years of Experience	0.021	0.011	0.088	1.91	0.057	1.48
Core Psychological Variables						
Creative Self-Efficacy (CSE)	0.110	0.018	0.256	6.11	<0.001	1.15
Technology Anxiety (TA)	-0.040	0.015	-0.109	-2.67	0.008	1.21
Aesthetic Sensitivity (AS)	0.018	0.022	0.034	0.82	0.413	1.12

Creative self-efficacy (CSE) exhibited the strongest positive predictive effect on AI-assisted design acceptance ($\beta = 0.256, p < 0.001$; see the scatterplot in Figure 10). This finding strongly suggests that designers with higher confidence in their innovative abilities are more likely to view AI as an empowering tool and to embrace its integration in their workflow.

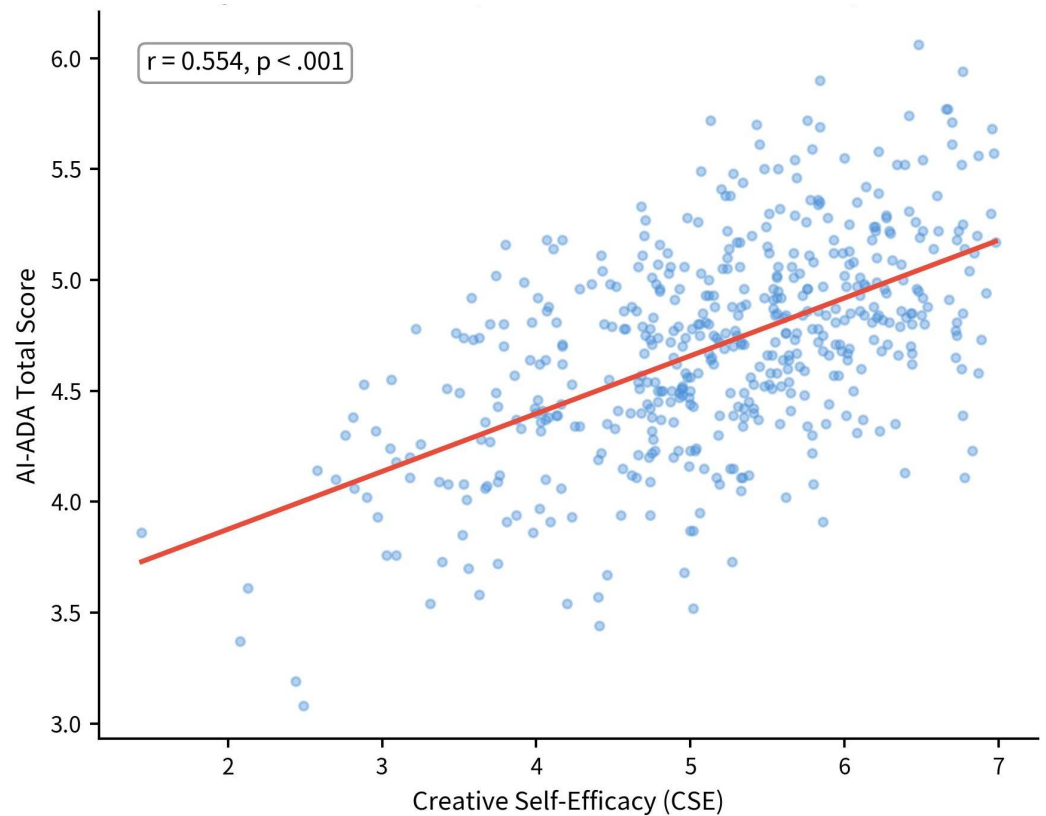


Figure 10. Relationship between CSE and AI Acceptance.

Technology anxiety (TA) showed a significant negative predictive effect ($\beta = -0.109$, $p = 0.008$; see Figure 11). The radar chart in Figure 12 further illustrates significant differences between high- and low-technology-anxiety groups across the four AI-ADAI subdimensions. Notably, participants with higher TA scored significantly lower on the Human-AI Co-creation dimension compared to those with lower TA, indicating that anxiety about technology reduces engagement in collaborative AI-driven creative processes.

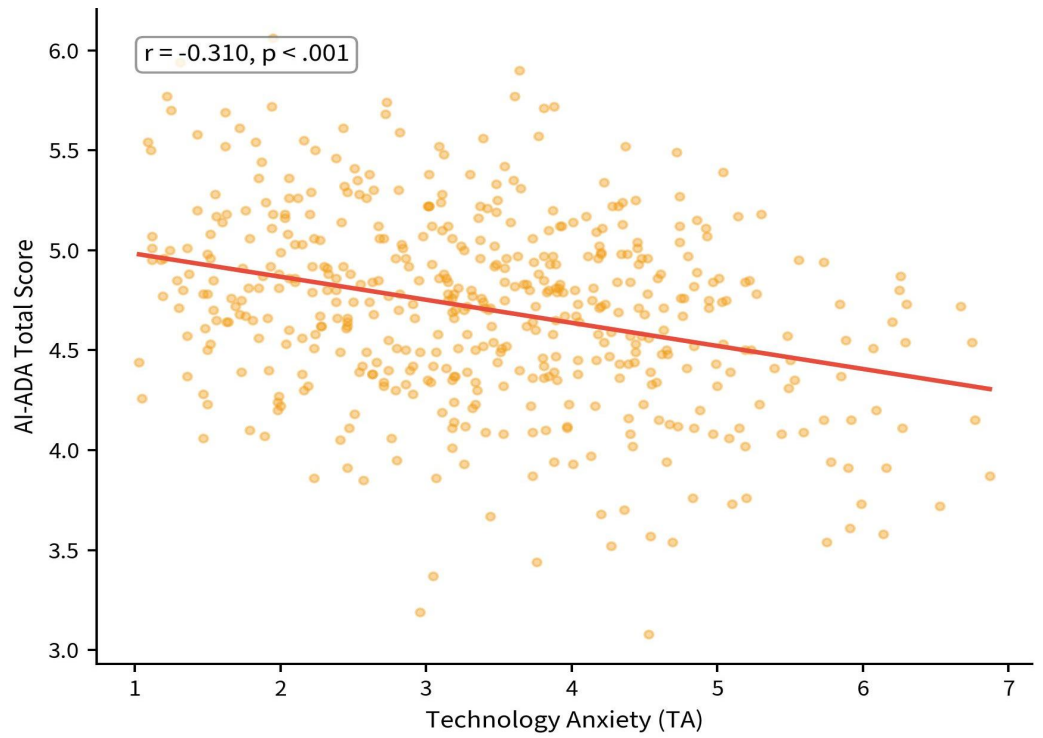


Figure 11. Relationship between TA and AI Acceptance.

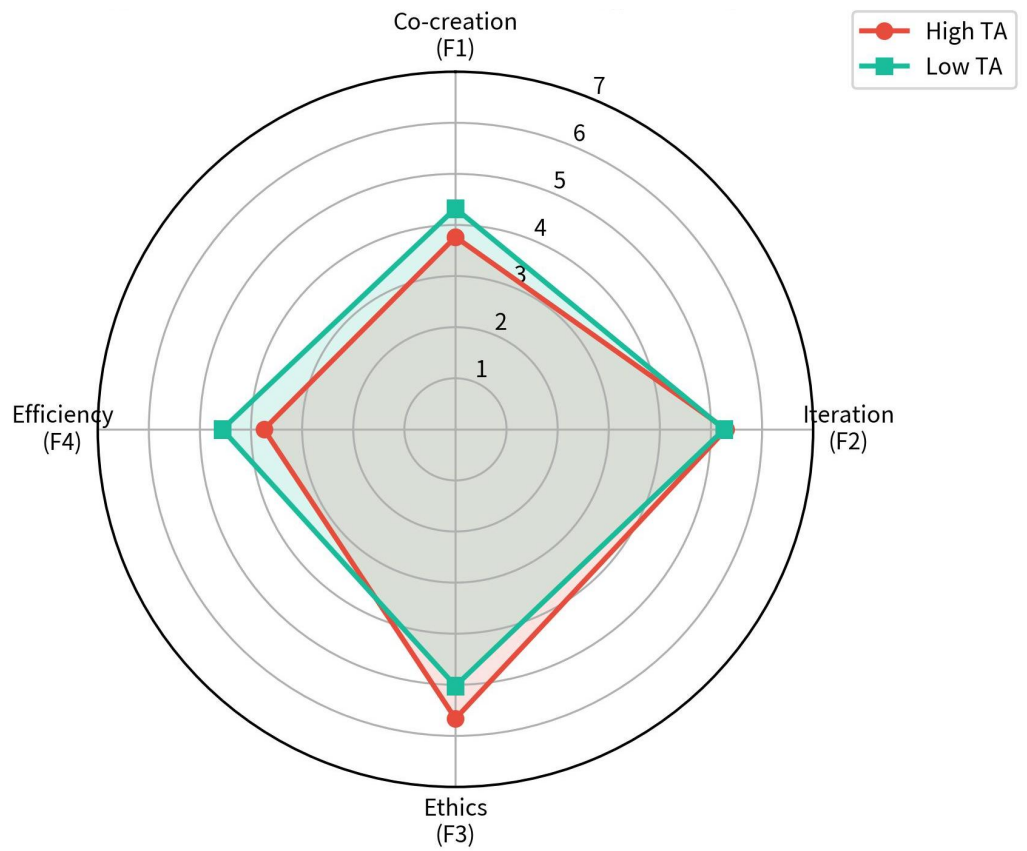


Figure 12. Factor Profiles by Technology Anxiety Level.

Aesthetic sensitivity (AS) did not show a significant main effect in the overall linear regression model ($p = 0.413$). However, based on prior theoretical

considerations, we conducted a nonlinear (quadratic) analysis. The results revealed a highly significant inverted-U relationship between AS and the Iterative Optimization (F2) subdimension (quadratic term coefficient negative and significant, $p < 0.01$; see Figure 13). Specifically, designers with moderately high levels of aesthetic sensitivity were most willing to leverage AI for iterative optimization. In contrast, designers with extremely high aesthetic sensitivity may reduce their use of AI in iterative processes, likely because current AI tools cannot fully meet their stringent and highly individualized aesthetic standards. This finding provides a nuanced understanding of how professional aesthetic judgment can influence engagement with AI in design tasks.

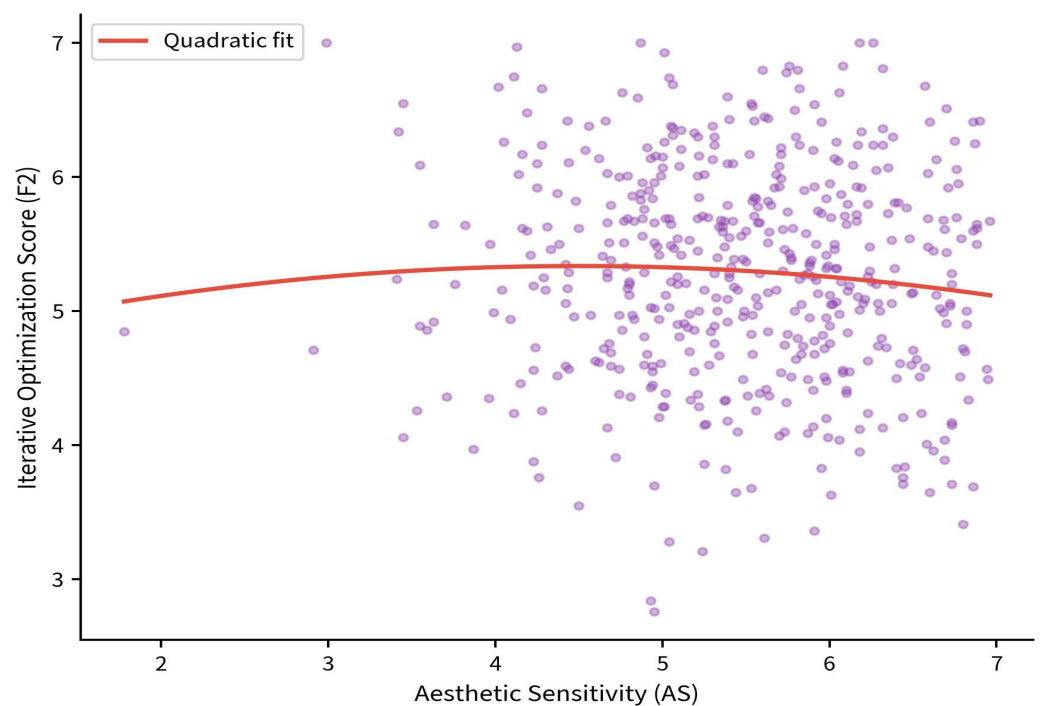


Figure 13. Curvilinear Relationship between AS and F2.

Figure 14 provides a visual summary of the standardized regression coefficients (β) for the three psychological traits across the AI-ADAI total score and its four subdimensions, clearly illustrating the differential contributions of each predictor.

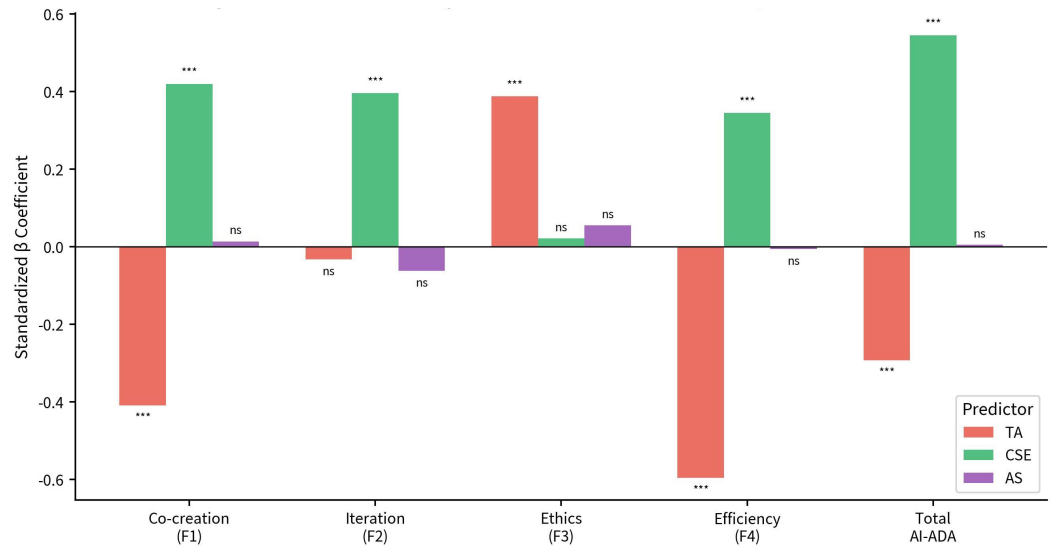


Figure 14. Standardized Regression Coefficients of Personality Traits on AI-ADA.

Figure 15 presents a Venn diagram depicting the core theoretical framework of this study, highlighting how technology anxiety, creative self-efficacy, and aesthetic sensitivity jointly influence AI-assisted design acceptance. This diagram emphasizes the interplay among these traits in shaping designers’ attitudes toward AI tools.

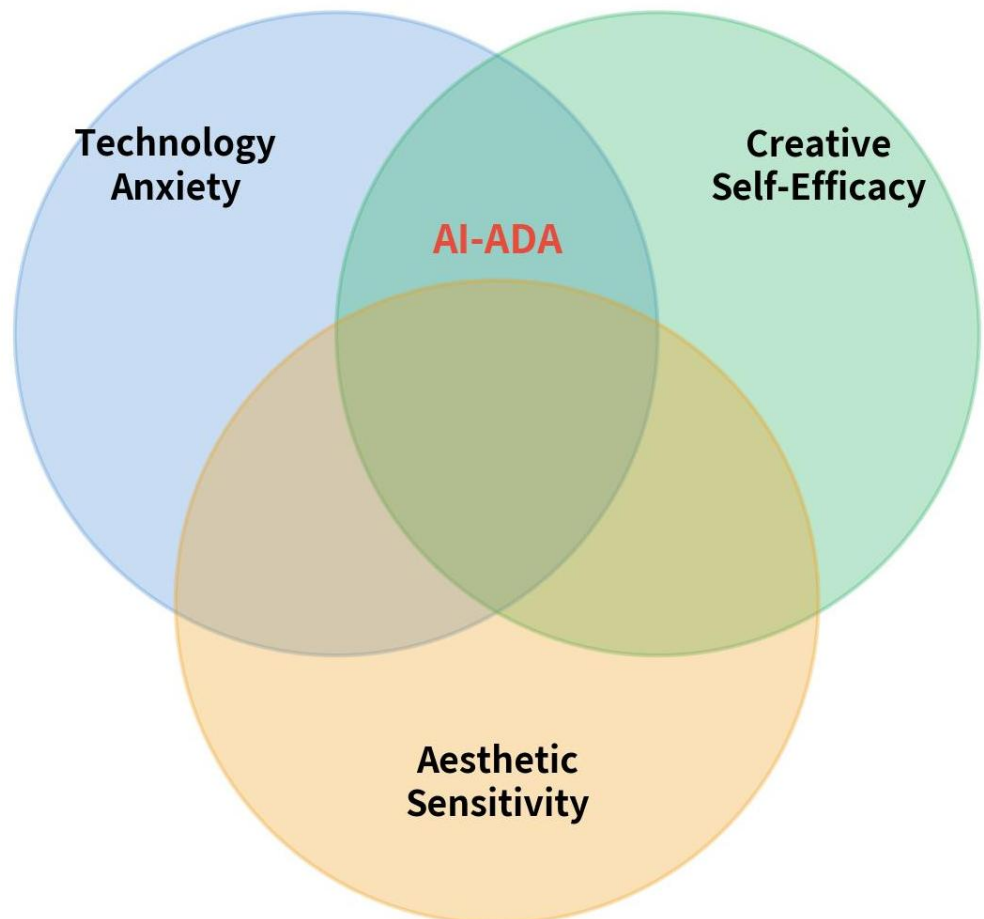


Figure 15. Venn Diagram of Three Personality Traits and AI-Assisted Design Acceptance.

5. Discussion

The primary aim of this study was not only to develop a reliable measurement instrument but also to use this tool to gain a deeper understanding of the underlying psychological mechanisms influencing designers’ responses to the rising wave of AI technologies. The results validated the multidimensional structure of the AI-ADAI scale and revealed the distinct pathways through which technology anxiety, creative self-efficacy, and aesthetic sensitivity shape AI acceptance.

5.1. Lateral Comparison of Theoretical Frameworks and Contributions

The four factors extracted in this study—Human-AI Co-creation, Iterative Optimization, Ethical & Copyright Awareness, and Design Efficiency Enhancement—differ substantially from traditional technology acceptance models, such as the perceived usefulness and perceived ease of use in the TAM framework. To clearly illustrate the theoretical contribution of this study, a lateral comparison between the AI-ADAI and classical models is presented in Table 6.

Table 6. Theoretical Comparison between AI-ADAI and Traditional Technology Acceptance Models (TAM).

Comparison Dimension	Traditional TAM (General-Purpose)	AI-ADAI (Design Context-Specific)	Key Differences / Interpretation
Technology Positioning	Passive Tool	Co-creator	While TAM views technology as an “amplifier” of user capability, AI-ADAI conceptualizes AI as a semi-autonomous collaborative partner.
Core Focus	Efficiency improvement, ease of use	Creative generation, iterative optimization, ethical awareness	Design involves not only task completion but also aesthetic judgment, value creation, and iterative exploration.
Application Scenarios	ERP systems, office software, deterministic tasks	Concept ideation, visual generation, highly ambiguous tasks	The nonlinear and subjective nature of design requires measurement tools that capture dynamic human-AI co-creation processes.
Psychological Preconditions	Behavioral Intention	Creative self-efficacy, aesthetic standards, copyright awareness	Designers’ AI acceptance is profoundly influenced by core professional competencies such as aesthetic sensitivity.

This comparison clearly indicates that, within the design context, simply evaluating whether a tool is “easy to use” is insufficient. Designers’ acceptance of AI

is deeply rooted in their understanding of the essence of design and in how they reposition themselves as creators within a human–AI collaborative framework.

5.2. Psychological Trait Differences and Underlying Mechanisms

The regression results revealed distinct pathways through which the three psychological traits influence AI–assisted design acceptance, offering rich theoretical insights into individual differences among designers:

- **Driving Role of Creative Self–Efficacy (CSE):** As the strongest positive predictor, designers with high creative self–efficacy demonstrated greater psychological resilience. They do not fear being replaced by AI but are confident in their ability to effectively harness AI. This finding supports the applicability of Bandura’s social cognitive theory in the context of human–AI co–creation [8];
- **Inhibitory Role of Technology Anxiety (TA):** The negative impact of technology anxiety extends beyond mere resistance to tools; it is particularly pronounced in the domain of Ethical & Copyright Awareness (F3). Highly anxious individuals tend to exaggerate potential negative consequences of AI use, such as copyright issues, thereby rationalizing their reluctance to adopt AI technologies;
- **The “Double–Edged Sword” Effect of Aesthetic Sensitivity (AS) – Inverted–U Relationship:** One of the most striking findings of this study is that designers with extremely high aesthetic sensitivity reduce their willingness to use AI for iterative optimization. This phenomenon can be attributed to the current technological ceiling. Top–tier designers possess highly individualized and exacting aesthetic standards, while contemporary generative AI tends to produce “averaged” or homogenized high–quality outputs. When AI outputs fail to meet these rigorous artistic expectations and fine–grained control at the pixel level is unachievable through prompt engineering, these highly sensitive designers may experience frustration, leading them to abandon AI as a primary iterative tool [13].

6. Conclusion

6.1. Summary of Key Findings

This study systematically developed and validated the AI–Assisted Design Acceptance Inventory (AI–ADAI), a 16–item scale encompassing four dimensions. Empirical analyses and rigorous psychometric assessments indicate that the scale demonstrates excellent reliability and validity, accurately capturing designers’ complex attitudes toward AI tools. Furthermore, the study confirms that:

- Creative self–efficacy serves as the primary intrinsic driver promoting AI acceptance;
- Technology anxiety acts as a major psychological barrier inhibiting AI adoption;

- Aesthetic sensitivity modulates designers’ willingness to utilize AI for iterative optimization through a complex nonlinear (inverted-U) relationship.

6.2. Practical Implications and Managerial Recommendations

From a practical perspective, this study provides actionable diagnostic tools and intervention strategies for design education and enterprise digital transformation initiatives (see Table 7). The findings suggest that fostering designers’ creative self-efficacy, alleviating technology-related anxieties, and tailoring AI tools to accommodate varying levels of aesthetic sensitivity can significantly enhance the integration of AI in design workflows.

Table 7. Practical Intervention Strategies Based on AI-ADAI Findings.

Target Group Characteristics	Psychological Profile / Diagnosis	Recommended Intervention & Management Strategy
High Technology Anxiety	Fear of being replaced; avoidance of AI use	Desensitization Training: Introduce AI gradually through low-risk, supportive tasks (e.g., data collection); emphasize AI’s role as an “assistant” rather than a “replacement”.
Low Creative Self-Efficacy	Lack of confidence; over-reliance on AI	Empowerment Education: Incorporate critical thinking exercises in design curricula; encourage designers to augment AI outputs with hand-drawn or deeply revised work to rebuild creative confidence.
Extremely High Aesthetic Sensitivity	Disdain for “homogenized” AI outputs; reluctance to adopt	Advanced Workflow Integration: Avoid forcing AI for final visual production; instead, guide designers to use AI as a moodboard generator or early-stage ideation tool.

6.3. Research Limitations and Future Directions

This study inevitably presents several limitations. First, regarding sample representativeness, although participants covered multiple subfields of design, the majority were from visual and interaction design. Future research should extend to areas such as industrial design and architecture, which involve greater physical constraints, to examine the cross-domain generalizability of the AI-ADAI scale. Second, this study relied on cross-sectional data, which cannot capture the dynamic evolution of designers’ attitudes in response to rapidly iterating AI tools (e.g., the transition from Midjourney V5 to V6). Future studies are strongly encouraged to adopt longitudinal designs, incorporating design performance metrics to further validate the causal relationships between AI-ADAI scores and the quality of final design outputs.

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