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When Creativity Encounters Algorithms: Personality Traits as Predictors of Design Students' Adoption and Dependence on AI-Assisted Design

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ABSTRACT

With the rapid development of generative AI, AI-assisted design tools are increasingly integrated into design education, yet students show marked differences in acceptance, continuance intention, and dependence. Given the creative nature of design learners, personality traits may strongly shape their responses to AI. This study examines how the Big Five influence attitudes toward AI-assisted design and how these attitudes drive continuance intention and AI dependence. Using PLS-SEM with data from 345 design majors, the model "Personality Traits → Attitude → Continuance Intention → AI Dependence" was tested. Conscientiousness positively predicts attitude, while extraversion, neuroticism, and openness negatively predict it; agreeableness shows no effect. These results indicate differing sensitivities to efficiency, uncertainty, and creative constraints in AI-generated outputs. Attitude significantly predicts continuance intention and directly and indirectly contributes to AI dependence. Overall, the study reveals personality's critical role in AI adoption and provides insights for developing personalized, human–AI collaborative design education.

Keywords: AI-assisted design, Big five personality traits, Technology adoption, Continuance intention, AI dependency

INTRODUCTION

With the rapid advancement of AIGC in visual creativity and conceptual exploration, AI-assisted design tools are reshaping design education and significantly enhancing students' efficiency and creative output (Huang et al., 2025). Yet design students differ markedly in their responses to AIGC—some readily adopt and depend on it, while others remain cautious or resistant. Although technology acceptance research highlights perceived usefulness and ease of use (Wang et al., 2024), it has largely overlooked stable personality traits, which are crucial in design contexts emphasizing aesthetic judgment, creative autonomy, and subjective expression. Despite the Big Five framework's extensive use in technology adoption studies, its applicability to AIGC—characterized by high generativity, uncertainty, and limited controllability—remains underexplored. Concerns over reduced creative control and authorship (Jago & Carroll, 2023), emerging AI dependence driven by psychological stickiness and capability reliance (Liu, 2025), and

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the context-specific effects of traits such as openness, agreeableness, and extraversion (Kumar et al., 2024) indicate that personality may shape attitudes and behaviors differently in creativity-intensive settings. To address these gaps, this study proposes an integrated pathway—"Big Five personality traits → attitude → continuance intention → AI dependence"—to explain how personality influences design students' evaluations and long-term use of AIGC. This framework advances understanding of creative technology adoption and offers insights for personalized pedagogy in AIGC-driven design education.

Related Work

The Big Five Personality Traits—extraversion, agreeableness, conscientiousness, neuroticism, and openness—are a widely used framework for explaining differences in technology acceptance, innovation adoption, and learning behaviours (John & Srivastava, 1999). In prior research, openness fosters exploration of new tools; extraversion enhances proactive engagement; agreeableness and conscientiousness support task involvement; whereas neuroticism heightens anxiety and risk perception, reducing acceptance of intelligent technologies (Devaraj et al., 2008; Kumar et al., 2024). In design education, these traits are also linked to creativity, collaboration, aesthetic judgment, and engagement with emerging technologies such as 3D modeling and generative design (George & Zhou, 2001; Paunonen & Ashton, 2001).

Given their relevance to creative work, the Big Five provide a robust foundation for examining design students' responses to AIGC-assisted design. Accordingly, this study develops the model "Big Five Personality Traits → Attitude → Continuance Intention and Dependence" to explain how personality shapes attitudes and long-term engagement with AIGC (See Figure 1).

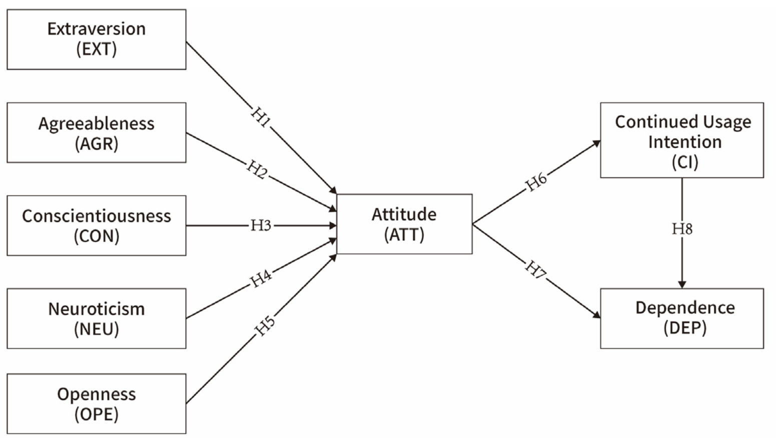

Figure 1: Proposed framework (created by the authors).

Extraversion—marked by sociability and proactivity—supports openness to new technologies and positive interaction experiences (Fu et al., 2024). Agreeableness, associated with empathy and cooperation, fosters favourable evaluations of collaborative tools (Dalvi-Esfahani et al., 2020; Devaraj et al., 2008). Conscientiousness aligns with the efficiency and workflow optimization offered by AIGC, such as rapid sketching and automated refinement (Barnett et al., 2015). In contrast, neuroticism—linked to emotional instability and risk sensitivity—reduces acceptance due to concerns about errors and loss of control (Wang et al., 2020; Li et al., 2024). Openness, characterized by curiosity and receptivity to novelty, encourages experimentation with innovative tools and inspiration from AI outputs (Goldberg, 2013; Li et al., 2024). Thus, we hypothesize:

H1: Extraversion positively influences attitude toward AI-assisted design.
H2: Agreeableness positively influences attitude toward AI-assisted design.
H3: Conscientiousness positively influences attitude toward AI-assisted design.
H4: Neuroticism negatively influences attitude toward AI-assisted design.
H5: Openness positively influences attitude toward AI-assisted design.

Attitude is a central predictor of technology adoption and continued use (Zhang et al., 2008). Positive attitudes enhance satisfaction, strengthen continuance intention (Bhattacherjee & Premkumar, 2004), and may directly increase reliance on AI tools (Turel & Serenko, 2012). Repeated and productive use further fosters functional and psychological dependence, making continuance intention a key mechanism in dependence formation (Turel, 2015). Therefore, we propose:

H6: Attitude positively affects continuance intention.
H7: Attitude positively affects AI dependence.
H8: Continuance intention positively affects AI dependence.

Questionnaire Design and Data Collection

The questionnaire comprised two parts: (1) demographic information (gender, age, and design specialization) and (2) measurement scales for the eight variables in the proposed model. All items were adapted from validated instruments in prior studies and assessed using a five-point Likert scale (1 = strongly disagree, 5 = strongly agree). Following expert review and a pilot test, the items were revised and finalized for the official survey.

Table 1: Measurement model.

Variables	CA	CR	AVE	Items	FL	VIF
Extraversion (EXT) (Laouiti et al., 2022)	0.831	0.854	0.660	EXT1	0.839	1.836
				EXT1	0.848	2.083
				EXT1	0.801	1.914
				EXT1	0.759	1.846
Agreeableness (AGR) (Laouiti et al., 2022)	0.815	1.062	0.621	AGR1	0.714	1.692
				AGR1	0.747	1.692
				AGR1	0.784	2.020
				AGR1	0.895	1.682

(Continued)

Table 1: Continued.

Variables	CA	CR	AVE	Items	FL	VIF
Conscientiousness (CON) (Laouiti et al., 2022)	0.830	0.956	0.646	CON1	0.779	1.679
				CON1	0.819	2.490
				CON1	0.904	1.956
				CON1	0.701	2.153
Neuroticism (NEU) (Laouiti et al., 2022)	0.874	0.916	0.722	NEU1	0.877	2.171
				NEU1	0.841	2.219
				NEU1	0.888	2.620
				NEU1	0.789	2.133
Openness (OPE) (Laouiti et al., 2022)	0.888	0.928	0.744	OPE1	0.787	2.114
				OPE1	0.868	2.670
				OPE1	0.941	4.191
				OPE1	0.848	2.714
Attitude (ATT) (Davis, 1989)	0.872	0.874	0.723	ATT1	0.818	2.437
				ATT1	0.894	3.288
				ATT1	0.854	2.265
				ATT1	0.833	1.981
Continuance Intention (CI) (Davis, 1989)	0.840	0.844	0.613	CI1	0.707	1.726
				CI1	0.839	2.125
				CI1	0.828	2.232
				CI1	0.823	2.271
				CI1	0.705	1.690
AI Dependence (DEP) (Morales-García et al., 2024)	0.864	0.921	0.700	DEP1	0.823	2.468
				DEP1	0.867	2.408
				DEP1	0.814	2.206
				DEP1	0.841	1.601

This study employed a snowball sampling approach targeting university students majoring in design-related disciplines. Data were collected via the online survey platform SoJump. A total of 345 valid responses were obtained. Detailed demographic information is presented in Table 2.

Table 2: Sample description.

Category	Options	Frequency	Percentage (%)
Gender	Male	135	39.13
	Female	210	60.87
Age	18–21	227	65.80
	22–25	118	34.20
Educational Level	Undergraduate	280	81.16
	Graduate student	65	18.84

(Continued)

Table 2: Continued.

Category	Options	Frequency	Percentage (%)
Major Type	Product Design / Industrial Design	81	23.48
	Environmental Design / Architectural & Environmental Art	50	14.49
	Visual Communication Design / Graphic Design	51	14.78
	Digital Media Art / Animation / Interaction Design	86	24.93
	Others	77	22.32

Data Analysis and Result

Common Method Bias

Common method bias refers to systematic, non-substantive variance that may distort relationships among variables in survey research and threaten the validity of empirical findings. To assess this issue, Harman's one-way test was conducted using SPSS 27.0. The analysis extracted eight factors with eigenvalues greater than 1, explaining 72% of the cumulative variance, while the first factor accounted for only 19%—well below the 40% threshold. These results indicate that common method bias is not a significant concern in this study (Podsakoff et al., 2003).

Reliability and Validity Analysis

This study used SmartPLS 4.1 to evaluate the measurement and structural models. All latent variables showed strong reliability, with Cronbach's α and Composite Reliability values exceeding 0.70, and all VIFs below 5, indicating no multicollinearity (Nunnally & Bernstein, 1994; Neter et al., 1990). Convergent validity was supported by standardized loadings above 0.70 and AVE values greater than 0.50 (Fornell & Larcker, 1981) (see Table 1). Discriminant validity was confirmed using the Fornell-Larcker criterion, as the square root of each construct's AVE exceeded its correlations with other constructs (see Table 3). Overall, the measurement model demonstrated solid reliability and validity, providing a strong foundation for structural model analysis.

Table 3: Fornell–Larcker criterion.

	DEP	EXT	AGR	CON	OPE	ATT	CI	NEU
DEP	0.812							
EXT	−0.146	0.788						
AGR	0.051	−0.176	0.804					
CON	0.187	−0.046	0.030	0.850				
OPE	−0.035	0.029	−0.159	−0.179	0.863			
ATT	0.391	−0.158	0.144	0.254	−0.153	0.850		
CI	0.453	−0.023	−0.010	0.114	−0.012	0.549	0.783	
NEU	−0.213	0.064	−0.064	−0.146	−0.011	−0.241	−0.109	0.837

Structural Model Assessment

The structural model was assessed using path coefficients and R^2 values, with Bootstrapping (5,000 resamples) performed in Smart-PLS 4.1. As shown in Table 4 and Figure 2, four hypotheses were supported: performance expectancy, effort expectancy, social influence, and hedonic motivation all showed significant positive effects on usage intention, supporting H1, H2, H3, and H5. In contrast, facilitating conditions did not significantly predict usage intention ($p > 0.05$), so H4 was not supported. The R^2 values indicate acceptable explanatory power: attitude (14.5%), continuance intention (30.2%), and dependence (23.4%), demonstrating that the model has good predictive validity (Sarstedt et al., 2017).

Table 4: A summary of the results of hypotheses testing.

Hypothesis	Original Sample (O)	Mean (M)	STDEV	T Statistics	P values	Result
EXT →ATT	−0.118	−0.133	0.048	2.480	0.013	Unsupport
AGR→ATT	0.088	0.100	0.067	1.307	0.191	Unsupport
CON→ATT	0.199	0.205	0.043	4.571	0.000	Support
NEU→ATT	−0.200	−0.204	0.051	3.882	0.000	Support
OPE→ATT	−0.102	−0.108	0.046	2.191	0.029	Unsupport
ATT→CI	0.549	0.550	0.045	12.164	0.000	Support
ATT→PED	0.342	0.345	0.058	5.878	0.000	Support
CI→DEP	0.203	0.203	0.055	3.686	0.000	Support

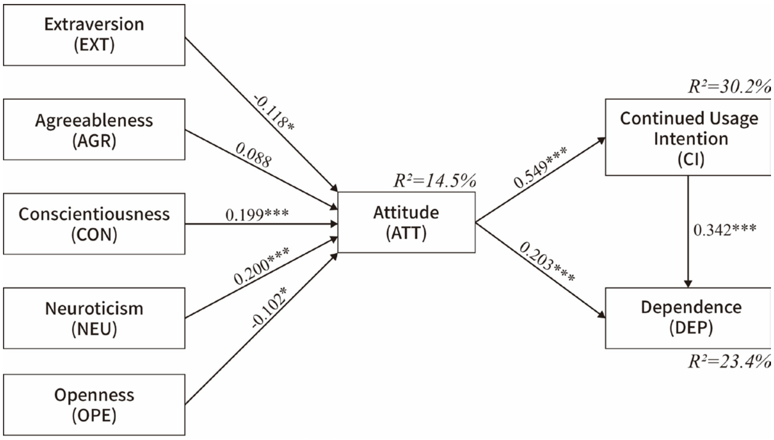

Figure 2: Results of model analysis (created by the authors).

Mediating Effect Test

To further clarify how attitude and continuance intention shape dependence, a mediation analysis was conducted. As shown in Table 5, attitude had a significant indirect effect on dependence through continuance intention. This indicates that attitude not only directly influences users' continued use but also indirectly fosters psychological dependence via continuance intention, supporting the chain mediation of "attitude → continuance intention → dependence."

Table 5: Indirect effects.

Paths	O	T	P	0.025	0.975	Result
ATT –> CI –> DEP	0.188	4.945	0.000	0.063	0.168	Support

DISCUSSION

Consistent with prior research (Devaraj et al., 2008; Li et al., 2024; Bhattacherjee & Premkumar, 2004; Turel & Serenko, 2012; Turel, 2015), the supported paths reveal the core psychological mechanisms linking personality, attitude, and behaviour in AIGC-assisted design, indicating that generative AI follows a distinct adoption logic. First, conscientiousness positively affects attitude. In line with Task-Technology Fit Theory (Goodhue & Thompson, 1995), conscientious individuals value order, efficiency, and controllability, which align with AIGC's workflow optimization and automation, enhancing perceived fit and evaluation. Second, neuroticism negatively affects attitude. AIGC's black-box nature and uncertain outputs heighten risk sensitivity among neurotic individuals, reducing acceptance—consistent with the "emotional stability-risk perception" mechanism (Meuter et al., 2003). Third, attitude strongly promotes continuance intention, consistent with TAM and ECM. Positive attitudes reflect perceived creative augmentation, reinforcing confirmation effects and motivating sustained use (Tella & Olasina, 2014). Finally, attitude and continuance intention jointly foster AI dependence, with continuance intention serving as a key mediator. Dependence emerges through repeated engagement, habit formation, and growing perceptions of AIGC's irreplaceability in creative and efficiency-related tasks. This process aligns with Media Dependence Theory (Ball-Rokeach & DeFleur, 1976), which outlines behavioural inertia and cognitive reinforcement as dual pathways to dependence. The indirect effect of "attitude → continuance intention → dependence" demonstrates AIGC's strong psychological stickiness in creative design. Overall, these findings confirm a sequential psychological chain of "personality → attitude → behaviour → dependence," showing that generative AI adoption reflects a deep process shaped by personality traits, risk judgments, and perceived creative control.

This study finds that extraversion, agreeableness, and openness do not significantly predict attitude, diverging from traditional technology acceptance findings and revealing the unique psychological mechanisms of AIGC in creative contexts. First, the nonsignificant effect of extraversion reflects strong context dependency. Extraverted individuals are motivated by social interaction, whereas AIGC tools emphasize individual creation without social cues. According to Trait Activation Theory, traits such as extraversion are not triggered when situational cues are absent (Tett & Burnett, 2003), explaining the lack of effect. Second, the nonsignificant effect of agreeableness suggests that social personality traits are less relevant in individualized creative tasks. AIGC use centers on personal style and aesthetic judgment rather than collaboration, aligning with Person–Task Fit Theory, which posits that prosocial traits matter only when task demands involve sociality (Barrick et al., 1998). Most notably, the nonsignificant effect of openness deviates from common findings in innovation adoption. Although openness reflects curiosity and novelty seeking, AIGC's style-driven outputs and potential creative substitution may weaken perceived creative control and evoke originality anxiety, thereby suppressing positive attitudes. This indicates that openness operates differently in creative domains, moderated by mechanisms such as perceived creative autonomy and aesthetic congruence—consistent with Self-Determination Theory. In sum, extraversion, agreeableness, and openness do not influence attitude because AIGC's core value lies in efficiency and generativity rather than social interaction, and its generative nature may threaten creative autonomy for highly open individuals. These findings suggest that conventional adoption predictors may be less applicable in creative contexts, underscoring the need for context-sensitive technology acceptance models.

This study contributes to creative-technology adoption research in three ways. First, applying the Big Five framework to AIGC-assisted design shows that conscientiousness and neuroticism shape attitudes via task-technology fit and risk sensitivity, extending personality explanations into creative technology contexts. Second, the nonsignificant effects of extraversion, agreeableness, and openness reveal boundary conditions of models like TAM and UTAUT, suggesting that AIGC's individualized workflows and algorithmic stylistic dominance alter the role of social and openness-related traits. Third, the study identifies a dual-path "attitude → behaviour → dependence" mechanism, demonstrating that AI dependence arises through both habitualization and attitude-driven valuation of AIGC's creative augmentation. Together, these insights refine theories of AI dependence and highlight the need for context-sensitive models of creative-technology acceptance.

This study offers several practical implications for design education and the pedagogical use of AIGC. The findings support personalized AIGC instruction: conscientious students benefit from structured, efficient workflows, whereas neurotic students require more predictable feedback to reduce anxiety, suggesting differentiated teaching strategies. Because attitude drives both continuance intention and dependence, educators should mitigate over-reliance on AI by incorporating balanced approaches such as AI-free creation stages, originality training, and pre-AI ideation. The results also inform tool development and industry deployment: risk-sensitive users require greater interpretability and controllability, while structure-oriented users benefit from stronger workflow integration. Enhancing these features may broaden adoption. Overall, this study provides actionable guidance for integrating AIGC into design education and improving user experience in the design industry.

This study has several limitations. The sample of mainland Chinese design majors restricts cultural and disciplinary generalizability; future work should include more diverse populations. The cross-sectional design cannot capture changes in attitudes and dependence, highlighting the need for longitudinal or experimental studies. Creative-domain factors such as perceived creative control, originality anxiety, and algorithmic trust were not assessed and may improve explanatory depth. Self-reported dependence may be affected by social desirability, suggesting the value of behavioral or qualitative data. Finally, differences among specific AIGC tools were not examined, indicating a need for tool- and task-specific analysis.

CONCLUSION

This study systematically demonstrates how personality traits shape design students' adoption and dependence on AI-assisted design. Using the Big Five framework, the findings reveal a sequential mechanism in which conscientiousness and neuroticism significantly influence attitudes through task-technology fit and risk sensitivity, whereas extraversion, agreeableness, and openness do not exhibit the expected effects found in traditional technology adoption contexts. These results highlight the contextual specificity of personality in creative domains, where aesthetic autonomy, originality concerns, and uncertainty tolerance play a pronounced role. Furthermore, attitude is shown to be a pivotal driver of continuance intention and a direct contributor to AI dependence. Continuance intention also mediates the development of dependence, indicating that repeated use, habit formation, and perceived irreplaceability jointly reinforce reliance on AIGC tools. This chain mechanism—"personality → attitude → continuance intention → dependence"—advances theoretical understanding of creative-technology adoption by revealing both cognitive–affective and behavioural pathways underlying AI reliance. Overall, this research provides new empirical evidence for the role of personality in AIGC-assisted design and offers practical implications for differentiated pedagogy, responsible AI integration, and the cultivation of balanced human–AI collaboration in design education.

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REFERENCES

Ball-Rokeach, S.J., DeFleur, M.L., 1976. A dependency model of mass-media effects. Commun. Res. 3, 3–21. https://doi.org/10.1177/009365027600300101

Barnett, T., Pearson, A.W., Pearson, R., Kellermanns, F.W., 2015. Five-factor model personality traits as predictors of perceived and actual usage of technology. European Journal of Information Systems 24, 374–390. https://doi.org/10.1057/ejis.2014.10

Barrick, M.R., Stewart, G.L., Neubert, M.J., Mount, M.K., 1998. Relating member ability and personality to work-team processes and team effectiveness. J. Appl. Psychol. 83, 377–391. https://doi.org/10.1037/0021–9010.83.3.377

Bhattacherjee, A., Premkumar, G., 2004. Understanding changes in belief and attitude toward information technology usage: a theoretical model and longitudinal test. MIS Q. 28, 229–254. https://doi.org/10.2307/25148634

Dalvi-Esfahani, M., Alaedini, Z., Nilashi, M., Samad, S., Asadi, S., Mohammadi, M., 2020. Students' green information technology behavior: beliefs and personality traits. J. Cleaner Prod. 257, 120406. https://doi.org/10.1016/j.jclepro.2020.120406

Davis, F.D., 1989. Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Q. 13, 319. https://doi.org/10.2307/249008

Devaraj, S., Easley, R.F., Crant, J.M., 2008. Research note—how does personality matter? Relating the five–factor model to technology acceptance and use. Inf. Syst. Res. 19, 93–105. https://doi.org/10.1287/isre.1070.0153

Fornell, C., Larcker, D.F., 1981. Evaluating structural equation models with unobservable variables and measurement error. J. Mark. Res. 18, 39–50.

Fu, P., Gao, C., Chen, X., Zhang, Z., Chen, J., Yang, D., 2024. Proactive personality and its impact on online learning engagement through positive emotions and learning motivation. Sci. Rep. 14, 28144. https://doi.org/10.1038/s41598–024–79776–3

George, J.M., Zhou, J., 2001. When openness to experience and conscientiousness are related to creative behavior: an interactional approach. J. Appl. Psychol. 86, 513–524.

Goldberg, L.R., 2013. An alternative "description of personality": The Big-Five factor structure. In: Personality and Personality Disorders. Routledge, pp. 34–47.

Goodhue, D.L. & Thompson, R.L., 1995. Task-technology fit and individual performance. MIS Quarterly, 19(2), pp. 213–236. https://doi.org/10.2307/249689

Huang, Z., Fu, X., Zhao, J., 2025. Research on AIGC-integrated design education for sustainable teaching: an empirical analysis based on the TAM and TPACK models. Sustainability 17, 5497. https://doi.org/10.3390/su17125497

Jago, A.S., Carroll, G.R., 2024. Who made this? Algorithms and authorship credit. Personal. Soc. Psychol. Bull. 50, 793–806. https://doi.org/10.1177/01461672221149815

John, O., 1999. The big-five trait taxonomy: history, measurement, and theoretical perspectives. Publ. as.

Kumar, A., Shankar, A., Nayal, P., 2024. Metaverse is not my cup of tea! An investigation into how personality traits shape metaverse usage intentions. J. Retail. Consum. Serv. 77, 103639. https://doi.org/10.1016/j.jretconser.2023.103639

Laouiti, R., Haddoud, M.Y., Nakara, W.A., Onjewu, A.-K.E., 2022. A gender-based approach to the influence of personality traits on entrepreneurial intention. J. Bus. Res. 142, 819–829. https://doi.org/10.1016/j.jbusres.2022.01.018

Li, H., Ren, T., Zhang, Z., 2025. Assistive tools or insecurity: the impact of technological readiness on willingness to use AI. Int. J. Hum.–Comput. Interact.

Li, H., Xue, T., Zhang, A., Luo, X., Kong, L., Huang, G., 2024. The application and impact of artificial intelligence technology in graphic design: a critical interpretive synthesis. Heliyon 10. https://doi.org/10.1016/j.heliyon.2024.e40037

Liu, J., 2025. When usefulness fuels fear: the paradox of generative AI dependence and the mitigating role of AI literacy. Int. J. Hum.–Comput. Interact. 0, 1–22.

Meuter, M.L., Ostrom, A.L., Bitner, M.J., Roundtree, R., 2003. The influence of technology anxiety on consumer use and experiences with self-service technologies. J. Bus. Res., Strategy in e-marketing 56, 899–906.

Morales-García, W.C., Sairitupa-Sanchez, L.Z., Morales-García, S.B., Morales-García, M., 2024. Development and validation of a scale for dependence on artificial intelligence in university students. Front. Educ. 9. https://doi.org/10.3389/feduc.2024.1323898

Neter, J., Wasserman, W. & Kutner, M.H., 1990. Applied Linear Statistical Models: Regression, Analysis of Variance, and Experimental Designs. 3rd ed. Homewood, IL: Irwin.

Nunnally, J.C. & Bernstein, I.H., 1994. *Psychometric Theory*. New York: McGraw-Hill.

Paunonen, S.V., Ashton, M.C., 2001. Big five factors and facets and the prediction of behavior. J. Pers. Soc. Psychol. 81, 524–539.

Podsakoff, P.M., MacKenzie, S.B., Lee, J.-Y., Podsakoff, N.P., 2003. Common method biases in behavioral research: a critical review of the literature and recommended remedies. J. Appl. Psychol. 88, 879–903. https://doi.org/10.1037/0021−9010.88.5.879

Sarstedt, M., Ringle, C.M. & Hair, J.F., 2017. Partial least squares structural equation modeling. Handbook of Market Research, 26(1), pp.1–40.

Tella, A., Olasina, G., 2014. Predicting users' continuance intention toward E–payment system: an extension of the technology acceptance model. Int. J. Inf. Syst. Soc. Change 5, 47–67. https://doi.org/10.4018/ijissc.2014010104

Tett, R., Burnett, D., 2003. A personality trait-based interactionist model of job performance. J. Appl. Psychol. 88, 500–517.

Turel, O., 2015. Quitting the use of a habituated hedonic information system: A theoretical model and empirical examination of facebook users. Eur. J. Inf. Syst. 24, 431–446.

Turel, O., Serenko, A., 2012. The benefits and dangers of enjoyment with social networking websites. Eur. J. Inf. Syst. https://doi.org/10.1057/ejis.2012.1

Wang, Q., Lau, R.Y.K., Yang, K., 2020. Does the interplay between the personality traits of CEOs and CFOs influence corporate mergers and acquisitions intensity? An econometric analysis with machine learning-based constructs. Decis. Support Syst. 139, 113424. https://doi.org/10.1016/j.dss.2020.113424

Wang, Q., Li, C., Zhu, L., 2024. Analysis on the acceptance of AIGC technology by art and design students in universities in China. Abac J. 44.

Zhang, P., Aikman, S.N., Sun, H., 2008. Two types of attitudes in ICT acceptance and use. Intl, J. Hum.–comput. Interact. https://doi.org/10.1080/10447310802335482