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The Acceptance of AI Tools Among Design Professionals: Exploring the Moderating Role of Job Replacement

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Article abstract

This study proposes a hypothetical model combining the unified theory of acceptance and use of technology (UTAUT) with self-determination theory (SDT) to explore design professionals' behavioral intentions to use artificial intelligence (AI) tools. Moreover, it incorporates job replacement (JR) as a moderating role. Chinese-speaking design professionals in regions influenced by Confucian culture were surveyed. An analysis of 565 valid cases with AMOS (Analysis of Moment Structures) supported the structural model hypothesis. The model explains 52.1% of the variance in behavioral intention to use (BIU), proving its effectiveness in explaining these variances. The results further validate the importance of performance expectancy (PE) over effort expectancy (EE) in influencing BIU. Additionally, it has been shown that the impact on intrinsic motivation (IM) and extrinsic motivation (EM) can be either amplified or diminished by anxiety about JR. For individuals experiencing higher levels of JR anxiety, there is a marked increase in IM. They may perceive adopting AI tools as an opportunity to enhance their skills and job security. Conversely, this anxiety also significantly boosts EM, as the potential for improved efficiency and productivity with AI use becomes a compelling incentive. These findings suggest new paths for academic researchers to explore the psychological impacts of AI on design professionals' roles. For practitioners, especially in human resources and organizational development, understanding these dynamics can guide the creation of training programs that address job replacement anxiety.

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Abstract

This study proposes a hypothetical model combining the unified theory of acceptance and use of technology (UTAUT) with self-determination theory (SDT) to explore design professionals' behavioral intentions to use artificial intelligence (AI) tools. Moreover, it incorporates job replacement (JR) as a moderating role. Chinese-speaking design professionals in regions influenced by Confucian culture were surveyed. An analysis of 565 valid cases with AMOS (Analysis of Moment Structures) supported the structural model hypothesis. The model explains 52.1% of the variance in behavioral intention to use (BIU), proving its effectiveness in explaining these variances. The results further validate the importance of performance expectancy (PE) over effort expectancy (EE) in influencing BIU. Additionally, it has been shown that the impact on intrinsic motivation (IM) and extrinsic motivation (EM) can be either amplified or diminished by anxiety about JR. For individuals experiencing higher levels of JR anxiety, there is a marked increase in IM. They may perceive adopting AI tools as an opportunity to enhance their skills and job security. Conversely, this anxiety also significantly boosts EM, as the potential for improved efficiency and productivity with AI use becomes a compelling incentive. These findings suggest new paths for academic researchers to explore the psychological impacts of AI on design professionals' roles. For practitioners, especially in human resources and organizational development, understanding these dynamics can guide the creation of training programs that address job replacement anxiety.

Keywords: unified theory of acceptance and use of technology, UTAUT, self-determination theory, generative artificial intelligence, GenAI, job replacement, performance expectancy

The Acceptance of AI Tools Among Design Professionals: Exploring the Moderating Role of Job Replacement

With the rapid popularization of generative artificial intelligence (AI) technology and the declaration of the year 2023 marking the breakout of generative artificial intelligence (GenAI), profound changes have occurred in various aspects of our daily lives (Aktan et al., 2022). GenAI can create various data, such as images, videos, audio, text, and three-dimensional models, and has significantly impacted fields such as science, education, medicine, technology, and business (Zhang & Aslan, 2021). In just 2 years, AI tools have sprung up rapidly, including text generators like ChatGPT and Bard; image generators such as Midjourney, Stable Diffusion, and DALL-E; and video generators including Runway and Lumen5. Among GenAI's various representative works, Chat Generative Pretrained Transformer (ChatGPT) stands out.

ChatGPT is noted as a premier AI tool in research (Korzyński, 2023) and commercialization (Dwivedi et al., 2023). Frey and Osborne predicted in 2017 that automation would have an impact especially in office and administrative support work. The industry professionals surveyed in this study, such as multimedia artists and animators, have a much lower probability of being affected by automation. However, the pace of AI advancement is often underestimated, and more powerful AI tools are continually emerging. AI tools specifically conceived for painting or design are meant to free designers from monotonous, low-value tasks, allowing them to focus on higher levels of creativity. Additionally, businesses benefit from cost savings and efficiency improvements (Du et al., 2023).

A Pew Research Center survey (Vogels, 2023) suggested AI will significantly impact young people's careers. This was highlighted by the 5-month U.S. Hollywood screenwriters' strike in 2023 over GenAI. Appleby (2023) found that 43% of students had experience using AI tools, and half admitted to relying on these tools for assignments and exams. ChatGPT, known for its capacity to produce responses resembling human language, should be approached cautiously. On the other hand, students who lack trust in technology might reject its use, missing out on learning opportunities. This is the key motivation for our study: understanding how the emerging use of AI tools affects the training and creative processes of students preparing to enter the design profession.

Historical data show that technology innovations trigger complex emotions (Gessl et al., 2019). Challenges include uncertainty in adaptation, trust issues, and AI anxiety, all of which hinders rational engagement (Rahman et al., 2022). Several theories have been proposed to explain and predict the acceptance and use of technology; the most notable are the technology acceptance model (TAM) (Davis, 1989) and the unified theory of acceptance and use of technology (UTAUT) (Venkatesh et al., 2003). Empirical tests have demonstrated that UTAUT 2 explained 74% of the variance in consumers' behavioral intention to use (BIU) and 52% of actual technology use (Venkatesh et al., 2016).

Duong et al. (2023) noted that effort expectancy not only directly affects students' actual use of ChatGPT but also indirectly increases their use through performance expectancy (PE) and the behavioral intention to use ChatGPT. PE and effort expectancy (EE) in UTAUT are similar to the perceived usefulness (PU) and perceived ease of use in the TAM, with its four constructs summarizing personal perceptions of technology (PE and EE) and environmental perceptions (social influence [SI] and facilitating condition [FC]) (Dwivedi et al., 2019). Because UTAUT requires many facets to explain a significant variance and the complexity of

SI and FC, potentially leading to inaccurate measurements (van Raaij & Schepers, 2008), in their 2008 study, van Raaij and Schepers initially overlooked the perception of the environment. In this research, we only extracted PE and EE from UTAUT.

The strength of UTAUT lies in its comprehensiveness in explaining the intrinsic connections among numerous psychological and social factors that may affect technology adoption, demonstrating applicability, validity, and stability in its collected data (Lin & Bhattacherjee, 2008). Therefore, in this study, motivation is considered an external variable within UTAUT, and we posit that motivational factors also affect the model's PE and EE. The motivation theory used in this study is based on the self-determination theory (SDT) proposed by Deci and Ryan (1985). Self-determination behavior includes three types of motivation: intrinsic motivation (IM), extrinsic motivation (EM), and amotivation. IM refers to the drive to act due to internal satisfaction, such as interest, fulfillment, and perceived utility; it becomes a powerful source of motivation when individuals can make autonomous decisions (Deci & Ryan, 1985). In contrast, EM is driven by the desire to achieve valuable external outcomes, such as improved job performance, knowledge acquisition, or a promotion; it can also be driven by a desire to avoid unwanted external outcomes, such as job replacement (JR) (Lawler & Porter, 1967; Wang & Wang, 2022). Amotivation refers to a lack of any intention to act. However, as our study's respondents had already used AI tools, there was no need to discuss amotivation.

Amabile (1993) suggested that there might be an interaction between IM and EM, yet research on such effects within UTAUT, particularly for technology acceptance, remains unexplored. Without a deep understanding of how IM and EM affect technology acceptance among design professionals, fully comprehending their intent to use AI tools amid AI advancements and job security concerns becomes unrealistic. For that reason, this study examines JR and its moderating role in the behavioral intention to use AI tools. JR anxiety refers to the anxiety caused by the concern that AI might replace people's current jobs (Wang & Wang, 2022; Wang et al., 2022).

The current research aims to address four gaps in the field. First, most AI tool use studies have centered on ChatGPT users (Duong et al., 2023; Rahman et al., 2022; Shahsavar & Choudhury, 2023), with relatively little research done on GenAI-related tools used by design professionals. Second, many studies have used UTAUT as their only theoretical framework, not deeply exploring vital motivational factors (Du et al., 2023; Shahsavar & Choudhury, 2023). Third, UTAUT's predictability differs by culture (King & He, 2006; Yoo et al., 2012), requiring more research on its use in various cultural contexts. Fourth, research on JR as a moderator between UTAUT and motivation types is limited and needs more investigation. To address these gaps, this study explores how the UTAUT framework and SDT relate, aiming to better understand design professionals' intent to use AI tools and JR's moderating role. Therefore, the study explores Confucian cultures within Chinese-speaking regions to assess UTAUT applicability in non-Western contexts, aiming to enhance its predictive accuracy.

Therefore, this study had three main objectives:

1. To investigate the factors influencing the behavioral intention to use AI tools among design professionals.

2. To develop an expanded UTAUT model that incorporates IM, EM, and JR in the context of AI tool usage.

3. To empirically validate the proposed model.

Hypotheses Development

Performance Expectancy (PE)

PE refers to an individual's anticipated level of improvement in job performance due to using a specific system (Venkatesh et al., 2003). Engel et al. (1995) and Chou et al. (2018) identified PE as a crucial predictor for mobile commerce. In this study, we operationally define PE as an individual's anticipation of improvement in one's ability to complete tasks, achieve goals, and efficiently alleviate their workload by using AI tools.

Studies have shown a close relationship between PE and BIU in the adoption of various technologies (Nikolopoulou et al., 2021). Therefore, we predict that the intention and action of design professionals to use AI tools will significantly grow with their increased PE. If AI tools can meet the PE of design professionals, they will become more attractive to them, making these professionals more willing to continue using AI tools. Based on the studies previously discussed, PE significantly influences design professionals' BIU AI tools. Hence, the following hypothesis was proposed:

H1: A positive relationship exists between PE and BIU in using AI tools.

Effort Expectancy (EE)

EE refers to the anticipated ease of using an information system (Nikolopoulou et al., 2021; Venkatesh et al., 2003), and it is closely related to the amount of effort required while using the system. Additionally, EE is viewed as a fundamental premise in predicting technology acceptance (Nikolopoulou et al., 2021).

Duong et al. (2023) found that EE directly influenced students' actual use of ChatGPT and indirectly increased their use through PE and the intention to use ChatGPT. Teo and Noyes (2014) discovered that EE affects consumers' behavioral intention to use technology. However, some studies found contrary results. Research on the adoption intention of mobile technology did not show a significant direct relationship between EE and BIU (Morosan & DeFranco, 2016). Thus, this remains an open issue worthy of attention.

In this study, EE is operationally defined as an individual's perception of ease and effortlessness in using AI tools. When design professionals perceive AI tools as seamless and efficient to use, they are more likely to integrate AI tools into their work. A positive perception of EE when using AI tools is a strong indicator significantly influencing design professionals' willingness to accept AI tools to optimize their design work. When the interface is friendly, intuitive, and easy to interact with, the possibility of user–system interaction increases (Duong et al., 2023). Thus, we proposed this hypothesis:

H2: A positive relationship exists between EE and BIU in using AI tools.

Intrinsic Motivation (IM)

According to Ryan and Deci (2000), people differ in their amounts of motivation and the types of motivation they experience. In other words, different individuals possess different motivational orientations, namely IM and EM, and varying levels of motivational intensity. Crucially, there is an interplay between IM and EM. IM refers to the driving force that originates from an individual, such as finding an activity exciting or challenging, instead of being driven by external stimuli, pressures, or rewards. Individuals can gradually develop IM when they can freely express their feelings under certain conditions.

In this study, IM refers explicitly to the psychological satisfaction that design professionals experience when using AI tools. Ryan and Deci (2000) noted that when people work in an environment that supports autonomy, they feel capable, which enhances IM. Thus, to maximize the intrinsic drive of design professionals, it is necessary for them to achieve goals and receive appropriate rewards for their work. However, it is also important to be aware that IM can be weakened by the forces of consistency in the environment, social recognition, and the reduction of expected tangible rewards.

Oliver (1974) found that EM can serve as an indicator for measuring PE. However, Tyagi (1985) argued that the impact of IM on PE is more significant compared to its effect on EE. In the study by Zhao et al. (2018), self-presentation was regarded as a second-order formative indicator of IM, and the authors noted that if Twitch could satisfy the intrinsic and extrinsic needs of the broadcasters, their PE would be strengthened and enhanced. Therefore, this study put forward the following hypotheses:

H3: A positive relationship exists between IM and PE in using AI tools.

H5: A positive relationship exists between IM and EE in using AI tools.

Extrinsic Motivation (EM)

EM guides the behavior taken by individuals to achieve specific outcomes, such as receiving external rewards (Ryan & Deci, 2000). Hars and Ou (2014) considered EM to include direct and indirect economic rewards and social recognition elements. Zhao et al. (2018) categorized anticipated extrinsic reward, self-esteem benefits, social benefits, and feedback as second-order formative indicators of EM, noting that if Twitch satisfied broadcasters' social benefits gained from audience feedback and interactions, it would directly impact their PE.

The theories of motivation by Rotter et al. (1972) and Overmier and Lawry (1979) demonstrated that people act only when they anticipate achieving a certain result, or they will choose actions that are valuable to them. Thus, EM primarily focuses on achieving outcomes or goals that are separate from the behavior itself. Based on this, the current study integrated the concept of EM with that of JR. Wang et al. (2022) showed that when people felt anxious about learning AI, their motivation to learn decreased because they could not perceive the practicality and enjoyment of learning AI. However, when people feared that AI might replace human jobs, it actually motivated them to learn AI. The motivation of design professionals to perceive their job as enhanced rather than replaced by AI contributes to increased EE. This encouragement prompts them to actively learn and engage with AI tools, providing more opportunities and fostering a positive perception of the tools' ease of use. Therefore, based on these findings, we propose the following hypotheses:

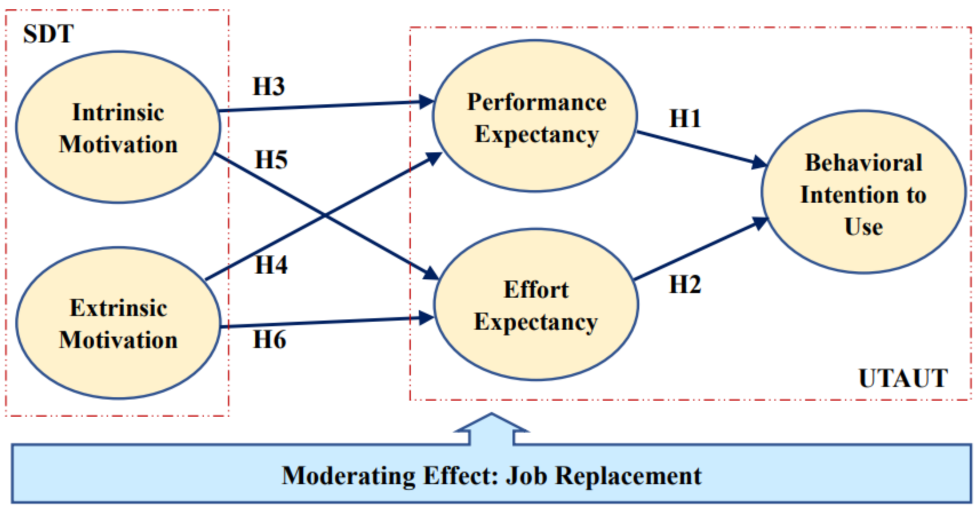
H4: A positive relationship exists between EM and PE in using AI tools.

H6: A positive relationship exists between EM and EE in using AI tools.

This study therefore study suggests that both IM and EM impact PE and EE, directly or indirectly affecting BIU to use AI tools. Additionally, JR is considered a moderating factor. The conceptual framework of this research is shown in Figure 1.

Figure 1

Research Model



Note. SDT = self-determination theory; UTAUT = unified theory of acceptance and use of technology.

Methodology and Research Design

Research Site and Sampling

This cross-sectional study, conducted from January 8 to 15, 2024, employed a self-administered online questionnaire to collect data from samples. The target respondents were users of AI tools in regions influenced by Confucian culture, specifically those with experience using AI for design-related tasks and who were part of the Chinese-speaking community. All respondents provided informed consent, and we guaranteed the confidentiality of their responses. The survey was created using Google Forms and an online platform named Wenjuanxing (https://www.wjx.cn/) and was distributed through social media platforms. The study protocol excluded individuals who (a) were under age 18 and (b) lacked prior experience with the AI tools in question. Among the 568 individuals who initially engaged with the survey, three questionnaires were filled out with only "strongly agree" or "strongly disagree" as responses to all questions. Therefore, we determined that the other 565 responses were considered valid and suitable for further data analysis. The demographic profile of these respondents is illustrated in Table 1.

Table 1

Demographic Profile of Respondents (n = 565)

Variable	Value label		Frequency	Valid %
Gender	1.	Male	232	41.06
	2.	Female	333	58.94
Age	1.	18–20	167	29.56
	2.	21–25	342	60.53
	3.	26–30	29	5.13
	4.	31–40	11	1.95
	5.	41+	16	2.83
Education	1.	Undergraduate design students	429	75.93
	2.	Graduate design students (Master's/PhD level)	67	11.86
	3.	Alumni with a design major	57	10.09
	4.	Design graduates (Master's/PhD-level alumni)	12	2.12
Frequency of using AI tools (times per week)	1.	1–3	212	37.52
	2.	4–6	193	34.16
	3.	7–10	106	18.76
	4.	11–15	27	4.78
	5.	16+	27	4.78
Anxiety of job replacement by AI	1.	Yes	268	47.43
	2.	No	297	52.57
		Total	565	100.00

Note. AI = artificial intelligence.

Instrument Development

This research measured the latent variables, as illustrated in Figure 1, using reflective latent constructs slightly adapted from prior studies (Duong et al., 2023; Engel et al., 1995; Hars & Ou, 2014; Morosan & DeFranco, 2016; Nikolopoulou et al., 2021; Overmier & Lawry, 1979; Rotter et al., 1972; Ryan & Deci, 2000; Teo & Noyes, 2014; Zhao et al., 2018). The hypotheses aimed to elucidate the nature of certain relationships or to identify differences among groups or the independence of two or more factors in a given scenario. Reflective constructs were selected because each latent variable was represented by multiple observed variables, which were considered manifestations of the underlying construct. This selection aligns with the capabilities of structural equation modeling (SEM) to rigorously test these complex relationships and to assess the reliability and validity of the constructs.

The questionnaire used in this study comprised structured, closed-ended questions. Respondents provided their answers based on their personal feelings and cognitions. The items were scored a 7-point Likert scale format. First, the questionnaire gathered basic respondent data such as gender, age, education, frequency of AI tool usage, and JR concerns. See Appendix for survey items.

Next, we focused exclusively on PE and EE. This decision was informed by the direct relevance of these constructs to our study's aims, their demonstrated impact on technology acceptance, and considerations of measurement reliability and validity within our specific research context. Each of these constructs comprised three items: PE, EE, and BIU (Duong, et al., 2023; Venkatesh et al., 2003; Venkatesh et al., 2012).

Last, we assessed design professionals' IM and EM for using AI tools based on the motivation structure emanating from SDT. We employed the motivation scale developed by Deci and Ryan (1985) and Deci et al. (2001), which has received global application and validation. Four items gauged IM and five items measured EM. The selection and adaptation of these items were informed by their established reliability and validity across various contexts. In addition, we integrated additional scale items from recent studies by Fan et al. (2012) and Wang et al. (2022). Overall, the measurement instrument incorporated a total of 21 items, and our research model consisted of five constructs.

Analysis Method

In this study, IBM SPSS 28 was employed for deriving descriptive statistics, conducting item analysis, and carrying out reliability and validity assessments. Additionally, SEM was performed using SPSS AMOS 26 to evaluate the fit of the research model. SEM is a robust statistical technique capable of simultaneously analyzing multiple regression equations and is notably prevalent in social work–related literature (Shek & Yu, 2014). This research focused on exploring the structural relationships between SDT and UTAUT, assessing both direct and indirect interactions among exogenous and endogenous variables within a complex structure, as guided by SEM analysis (Barbara, 1998; Kline, 2005).

Empirical Analysis and Results

Sample Profile

The research encompassed a sample size of 565 individuals (Table 1). In terms of gender, female participants accounted for the largest number (333, 58.94%). In regard to age, the 21–25 group was the largest (342, 60.53%). Regarding education, undergraduate design students composed the highest number (429, 75.93%). Regarding use of AI tools, the group using AI one to three times per week had the largest number (212, 37.52%). In response to JR, the group responding "No" accounted for the largest number (297, 52.57%).

Model Reliability and Validity

Reliability and Convergent Validity

Table 2 shows that the absolute value of skewness is less than 2 and the absolute value of kurtosis is less than 7 (Kline, 2005). Thus, the data are normally distributed. The item PE01 had the highest mean (5.742), while EM03 had the lowest (5.067). That is, the respondents agreed the most with PE01 and disagreed the most with EM03.

All constructs exhibited strong composite reliability and average variance extracted (AVE), meeting recommended standards (Fornell & Larcker, 1981; Hair et al., 2019). See Table 2 for details on standard deviations and composite reliabilities in the range of .800 to .851. These results confirm acceptable convergent validity.

Table 2

Statistics for Each Construct

Construct	Item	*M*	*SD*	Skewness	Kurtosis	Std.	CR	AVE
IM	IM01	5.442	1.271	−0.754	0.357	0.719	0.841	0.569
	IM02	5.382	1.322	−0.858	0.759	0.782		
	IM03	5.412	1.279	−0.811	0.431	0.757		
	IM04	5.524	1.178	−0.890	1.436	0.758		
EM	EM01	5.579	1.170	−1.048	1.755	0.757	0.836	0.509
	EM02	5.381	1.308	−0.682	0.136	0.739		
	EM03	5.067	1.338	−0.404	−0.027	0.667		
	EM04	5.465	1.423	−0.972	0.562	0.568		
	EM05	5.736	1.173	−1.197	1.865	0.810		
PE	PE01	5.742	1.121	−1.572	4.200	0.790	0.849	0.585
	PE02	5.476	1.261	−0.824	0.732	0.767		
	PE03	5.674	1.194	−1.201	2.032	0.758		
	PE04	5.657	1.194	−0.971	1.333	0.743		
EE	EE01	5.265	1.292	−0.701	0.542	0.731	0.800	0.501
	EE02	5.287	1.292	−0.654	0.357	0.742		

	EE03	5.127	1.278	−0.583	0.179	0.670		
	EE04	5.280	1.269	−0.756	0.640	0.685		
BIU	BIU01	5.418	1.214	−0.836	0.998	0.790	0.851	0.588
	BIU02	5.297	1.295	−0.753	0.346	0.766		
	BIU03	5.458	1.241	−0.905	0.907	0.716		
	BIU04	5.471	1.276	−0.841	0.639	0.793		

Note. Std. = standardized factor loadings; CR = composite reliability; AVE = average variance extracted; IM = intrinsic motivation; EM = extrinsic motivation; PE = performance expectancy; EE = effort expectancy; BIU = behavioral intention to use.

Discriminant Validity

Discriminant validity, assessed following Fornell and Larcker's (1981) method, confirms that all AVE values exceed correlation coefficients (Table 3). The report found that the correlation between IM and PE is slightly larger than the AVE root value of PE, but the difference is only 0.017 (< 0.1) which can be viewed as a negligible correlation based on random sampling error (Schober et al., 2018). The result still shows great discriminant validity among constructs.

Table 3

Results of Discriminant Validity by Average Variance Extracted

	AVE	IM	EM	EE	PE	BIU
IM	.569	**.754**				
EM	.509	.616	**.713**			
EE	.585	.578	.509	**.765**		
PE	.501	.725	.671	.507	**.708**	
BIU	.588	.723	.622	.528	.630	**.767**

Note. AVE = average variance extracted; IM = intrinsic motivation; EM = extrinsic motivation; EE = effort expectancy; PE = performance expectancy; BIU = behavioral intention to use. The items in bold represent the square roots of the AVE; off-diagonal elements are the correlation estimates.

Model Fit

Whittaker and Schumacker (2022) recommend reporting nine widely accepted fitness metrics to assess model fit. A good model fit typically results in a Chi-square value/degrees of freedom ratio below 3. Additionally, Hu and Bentler (1999) recommend evaluating each fitness metric independently and controlling type I errors with more demanding model fit metrics, such as the comparative fit index (> .90), standardized root mean square residual (< .08), and root mean square error of approximation (< .08) (Table 4).

Table 4

Model Fit

Model fit	Criteria	Model fit of research model
ML χ^2	The smaller the better	487.430
df	The larger the better	182
Normed χ^2 (χ^2/df)	$1 < \chi^2/df < 3$	2.678
RMSEA	< .08	.055
SRMR	< .08	.048
TLI (NNFI)	< .90	.938
CFI	< .90	.946
GFI	< .90	.924
AGFI	< .90	.904

Note. ML = maximum likelihood; RMSEA = root mean square error of approximation; SRMR = standardized root mean square residual; TLI =Tucker-Lewis index; NNFI =non-normed fit index; CFI = comparative fit index; GFI =goodness of fit index; AGFI = adjusted goodness of fit index.

Path Analysis

In Table 5, the results of path analysis demonstrate significant associations among the constructs. For instance, PE ($\beta = 0.575$, $p < .001$) and EE ($\beta = 0.292$, $p < .001$) significantly affected BIU. The combined influence of these values explained 52.1% of the variance of BIU. IM ($\beta = 0.511$, $p < .001$) and EM ($\beta = 0.367$, $p < .001$) significantly affected PE. The combined influence of these values explained 65.3% of the variance of PE. IM ($\beta = 0.460$, $p < .001$) and EM ($\beta = 0.264$, $p < .001$) significantly affected EE. The combined influence of these values explained 39.5% of the variance of EE (Figure 2).

Table 5

Regression Coefficients

Hypothesis	DV	IV	Unstd.	*SE*	Unstd./*SE*	*p*	Std.	R^2	Result
H1	BIU	PE	0.575	0.057	10.015	.000	.531	.521	Supported
H2		EE	0.292	0.052	5.649	.000	.288		Supported
H3	PE	IM	0.511	0.054	9.453	.000	.528	.653	Supported

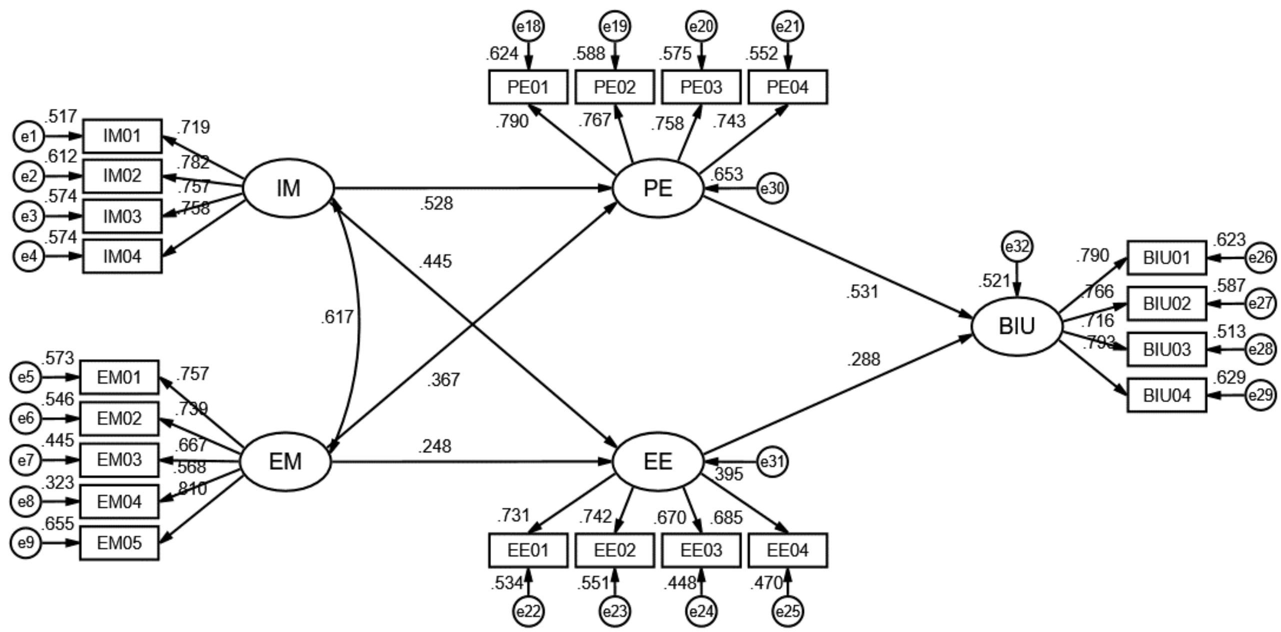
H4		EM	0.367	0.052	7.110	.000	.367		Supported
H5	EE	IM	0.460	0.067	6.838	.000	.445	.395	Supported
H6		EM	0.264	0.065	4.041	.000	.248		Supported

Note. DV = dependent variable; IV = independent variable; Unstd. = unstandardized factor loadings; SE = standard error; Std. = standardized factor loadings; BIU= behavioral intention to use; PE = perceived effort; EE = expected effort; IM = intrinsic motivation; EM = extrinsic motivation.

*** $p < .001$.

Figure 2

Structural Equation Modeling



Note. IM = intrinsic motivation; PE = perceived effort; BIU = behavioral intention to use; EM = extrinsic motivation; EE = expected effort.

Mediation Effects

The bootstrapping method is most commonly used to examine the indirect effect of intermediary variables. It is statistically more powerful than causal path methods and coefficient product methods (Williams & MacKinnon, 2008). Confidence intervals for indirect effects obtained through bootstrapping are statistically stable. However, when 0 is not found within the CIs' lower and upper bounds, bias correction from bootstrapping is suggested (Briggs, 2006; Williams & MacKinnon, 2008).

As shown in Table 6, the total effect IM→BIU, $p < .05$, bias-corrected CI does not include 0. The existence of total effect was supported. The specific indirect effect IM→PE→BIU, $p < .05$, bias-corrected CI does not include 0. Thus, the hypothesis that the existence of a specific indirect effect was supported. The specific indirect effect IM→EE→BIU, $p < .05$, bias-corrected CI does not include 0. Thus, the hypothesis that the existence of a specific indirect effect was supported.

The total effect EM→BIU, $p < .05$, bias-corrected CI does not include 0. The existence of total effect was supported. The specific indirect effect EM→PE→BIU, $p < .05$, bias-corrected CI does not include 0. Thus, the hypothesis that the existence of a specific indirect effect was supported. The specific indirect effect EM→EE→BIU, $p < .05$, bias-corrected CI does not include 0. Thus, the hypothesis that the existence of a specific indirect effect was supported.

Table 6

Mediating Effects

Effect	Point estimate	Product of coefficients			Bootstrap 1,000×	
		SE	*Z*	*p*	Bias-corrected 95% CI	
					Lower bound	Upper bound
Total effect						
IM→BIU	.429	0.082	5.210	.000	0.291	0.603
Specific indirect effect						
IM→PE→BIU	.294	0.085	3.456	.001	0.144	0.479
IM→EE→BIU	.134	0.062	2.165	.030	0.054	0.311
Total effect						
EM→BIU	.289	0.071	4.078	.000	0.156	0.441
Specific indirect effect						
EM→PE→BIU	.211	0.065	3.258	.001	0.101	0.356
EM→EE→BIU	.077	0.038	2.044	.041	0.023	0.182

Note. IM = intrinsic motivation; BIU = behavioral intention to use; PE = perceived effort; EE = expected effort; EM = extrinsic motivation.

Moderator Effects: Job Replacement

To examine the impact of concerns about job replacement, this study categorized responses into "Yes" (indicating anxiety about job replacement) and "No" (indicating no anxiety about job replacement). "Job replacement anxiety" was used as a moderator. Tables 7 and 8 display JR coefficients for these two groups. Out of the six slope comparisons, the IM to PE, IM to EE, and EM to PE comparisons reached statistical significance. Notably, the IM to PE and IM to EE coefficients are higher for "Yes." The EM to PE coefficient is higher for "No."

Table 7

Job Replacement Estimates

IV	DV	Yes (268)				No (297)			
		Estimate	*SE*	*Z*	*p*	Estimate	*SE*	*Z*	*p*
PE	BIU	.568	0.091	6.222	.000	.583	0.074	7.911	.000
EE	BIU	.239	0.079	3.045	.002	.320	0.070	4.599	.000
IM	PE	.582	0.069	8.431	.000	.333	0.088	3.768	.000
IM	EE	.566	0.087	6.497	.000	.271	0.109	2.480	.013
EM	PE	.276	0.058	4.784	.000	.562	0.102	5.514	.000
EM	EE	.218	0.076	2.874	.004	.355	0.120	2.958	.003

Note. IV = independent variable; DV = dependent variable; PE = perceived effort; BIU = behavioral intention to use; EE = expected effort; IM = intrinsic motivation; EM = extrinsic motivation.

Table 8

Job Replacement of Nested Model Differences

Model	Model fit				Nested model differences		
	NPAR	χ^2	*df*	χ^2/df	Δdf	$\Delta\chi^2$	*p*
Default	98	756.072	364	2.077			
PE→BIU	97	756.088	365	2.071	1	0.016	.900
EE→BIU	97	756.609	365	2.073	1	0.537	.464
IM→PE	97	760.830	365	2.084	1	4.757	.029
IM→EE	97	760.473	365	2.083	1	4.401	.036
EM→PE	97	762.544	365	2.089	1	6.472	.011
EM→EE	97	757.015	365	2.074	1	0.943	.332

Note. NPAR = number of parameters; PE = perceived effort; BIU = behavioral intention to use; EE = expected effort; IM = intrinsic motivation; EM = extrinsic motivation.

Discussion and Conclusions

Key Findings

The statistical analysis in Chapter 4 of this dissertation showed that PE and EE significantly and positively impacted the intention to use AI tools. IM and EM also significantly and positively affected PE and EE. The study identified four mediating effects: PE and EE mediate the relationship between IM and BIU, and both also mediate between EM and BIU. Furthermore, three significant moderation effects were found: JR moderates the effects of IM on PE and EE, as well as the effect of EM on PE. This study developed a relationship model covering four major aspects. The overall structural model demonstrated goodness of hit, and hypotheses 1–6 were supported. For the endogenous latent variables of BIU, PE, and EE, the R^2 values reached 52.1%, 65.3%, and 39.5%, respectively. The study's research model can therefore effectively explain these variables' variance.

The findings of this study indicate that PE and EE significantly and positively impacted design professionals' willingness to use AI tools. This aligns with the original hypotheses of the UTAUT model (Venkatesh et al., 2003). PE and EE have been confirmed as key factors influencing behavioral intentions (Davis, 1989; Venkatesh & Davis, 2000). This means that when design professionals believe AI tools can effectively complete tasks and are convenient, their willingness to use them increases. This result is consistent with current research findings on the behavioral intention to use GenAI tools (Du & Gao, 2023; Duong et al., 2023; Shahsavar & Choudhury, 2023).

In addition, this study uncovered a relatively less discussed phenomenon: IM and EM can positively influence design professionals' perceptions of PE when using AI tools. Through SDT, this research showed how, without external pressures and distractions, individuals' needs for internal growth and psychological needs can be met (Deci & Ryan, 2000). Additionally, this study introduces a relatively new hypothesis: IM and EM are hypothesized to positively influence design professionals' EE toward AI tools. Tyagi (1985) suggested that the impact of IM on PE is more significant than on EE; the results of this study show a similar trend. However, design professionals' positive perception of EE significantly increased when AI tools met their IM and EM needs.

The first mediator in the link from IM to BIU involves mediation. The effect of PE mediating between IM and BIU is over twice as strong as that of EE. This shows PE's greater importance compared with EE, as seen in studies by Shahsavar and Choudhury (2023) and Zhao et al. (2018), where only PE is considered. Another mediator is from EM to BIU: PE's mediating effect between EM and BIU is three times stronger than EE's. This further proved PE's substantial impact on BIU.

In the moderation aspect, the results revealed a notable phenomenon: for design professionals who expressed concerns about AI tools potentially replacing human jobs, IM had a stronger effect on PE and EE (Tables 7 and 8). This suggests that when job security is perceived as threatened, IM plays a more crucial role in enhancing PE and EE**.** In contrast**,** for those not worried about AI tools replacing jobs, the increasing influence of EM on PE is also thought-provoking. Design professionals concerned about job security seemed more inclined to boost their self-efficacy by enhancing their needs for relatedness, competence, and autonomy (Ryan & Deci, 2000), leading to a higher acceptance of AI tools. Thus, the study showed that concerns about JR (a moderating variable) amplified the influence of IM on PE and EE.

The participants' anxiety about JR due to AI is considered facilitating anxiety (Alpert & Haber, 1960) that positively affected IM. This study's results are partially contrary to those of Wang et al. (2022). In the study by Wang et al. (2022), EM, but not IM, was found to have a positive effect on the participants. This contrasts with the findings of Donnermann et al. (2021), in which there was no significant correlation between IM and PU, where PU is equivalent to PE. However, our findings indicate that JR anxiety among design professionals has a positive impact on both EM and IM. We also found that those with lower JR anxiety had higher EM than people with higher levels of anxiety. We found that people with higher JR anxiety due to AI had stronger IM, which is consistent with Piniel and Csizér's (2013) results showing that individuals with higher degrees of facilitating anxiety were found to invest more effort and persistence into learning professional knowledge and skills.

Statistics from Tables 7 and 8 indicate that the effect of EM on PE is significant. Consequently, anxiety about JR due to AI had a more significant impact on the pleasure of learning itself than on the rewards of learning AI-related skills, thus relatively weakening the influence on EM. The following are possible reasons for this. First, Confucianism, promoting moderation, seeks a balance between AI technology and the human, stressing that tech progress should boost social harmony and human growth. Work is a livelihood meant to fulfill personal values and duties (Zhu, 2020). Second, design professionals have higher professional confidence than the general public, which we will detail in section of Practical Implications.

JR anxiety has a dual effect on IM and EM, either boosting or lessening it. This resonates with previous studies on technology avoidance attitudes and behaviors (Huang & Haried, 2020; Maduku et al., 2023). This research innovatively reveals the varied impacts within the model, examining how JR influences design professionals' attitudes toward using AI tools. To our knowledge, this topic has yet to be discussed. Furthermore, we discovered that the moderating role of JR in intrinsic and extrinsic motivation differs significantly.

Theoretical Implications

This study has four main theoretical implications. First, the empirical results provide additional evidence that clarifies the relationship between design professionals and AI tools under the integration of UTAUT and SDT, offering a more comprehensive perspective on how design professionals accept and use AI tools. Second, the study confirms the importance of IM and EM for technology acceptance and usage intentions, further revealing how motivational factors affect BIU through PE and EE. This underscores the necessity of considering motivational factors in technology acceptance research. Third, this study is the first to explore the role of JR anxiety as a moderating variable in using AI tools, finding that JR concerns affect the relationship between IM and EM and behavioral intentions. This offers new theoretical insights into psychological factors in technology acceptance. Fourth, by focusing on AI tools, this research provides a deeper understanding of AI technology acceptance and use behavior, specifically in design professionals. This helps us theoretically understand how professionals accept emerging technologies.

Practical Implications

The design industry is a highly specialized and innovative organization where, in addition to professionals needing keen observation and skillful hands, the integration of AI technology is an inevitable trend in the modern era. Through this study's understanding of design professionals' behavioral intentions to use AI tools, developers and marketers can more accurately design and promote AI tools to meet their actual needs and expectations. The primary focus is on improving PE and EE, while design firm managers should focus on intrinsic and extrinsic motivations. Given the positive impact of IM and EM on enhancing PE and EE, design companies should devise effective incentive strategies to encourage employees to learn and use AI tools. For instance, appropriate training could be provided to reduce professionals' learning curve in using these tools, and practical reward systems could be offered to drive the successful implementation of technological innovations.

This research showed that concerns about JR significantly affect the acceptance and use of AI tools. Organizations and managers should recognize this concern and mitigate employees' fear of AI replacing human jobs through education and training, emphasizing the role of AI tools as assistants to enhance work efficiency rather than replacements for humans. More importantly, managers can promote an innovative culture within the organization, always remaining attentive to employees' psychological changes. After all, the design field is also a highly competitive industry, and striving for performance in the market requires good technical and psychological qualities.

Limitations and Future Research

We point out four main limitations of our study. First, although our results support the proposed model on how design professionals use AI tools and the important role of JR in this, we need more research to confirm these findings. Second, our model of AI-induced JR does not consider cultural elements. We gathered data through a network survey from people familiar with AI tools used by design professionals in Confucian cultures and Chinese-speaking areas. It is unclear if this model and the survey questions work well for people in different regions. Third, the current study is cross-sectional, meaning its scope is limited because it only captures the thoughts and intended actions of design professionals at a single time. It is known from research that such perceptions and behavioral intentions can change, particularly with the rapid development of GenAI tools. Fourth, we did not make any conclusions or suggestions about learning. Future studies should investigate how teachers with design backgrounds are dealing with the quick arrival of GenAI tools in higher education and how these AI tools impact their teaching.

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Appendix

Measurement Items and Sources

Construct	Items	Scale reference
Intrinsic motivation (IM)	IM01: I find the actual process of using AI tools to be enjoyable. IM02: Using AI tools enhances my personal development. IM03: I find it interesting to use AI tools to solve my design task problems. IM04: I believe using AI tools can be immensely beneficial to me.	Deci & Ryan (1985); Deci et al. (2001); Wang et al. (2022)
Extrinsic motivation (EM)	EM01: Using AI tools can improve my work performance. EM02: Using AI tools helps enhance my design knowledge. EM03: Using AI tools can assist in achieving higher income in the future. EM05: Overall, I find AI tools to be very useful for my learning.	Deci & Ryan (1985); Deci et al. (2001); Fan et al. (2012); Wang et al. (2022)
Performance expectancy (PE)	PE01: Using AI tools has increased my learning efficiency. PE02: AI tools can help me achieve my goals. PE03: Using AI tools gives me more opportunities to gain knowledge and skills. PE04: I find AI tools very useful in my daily life.	Venkatesh et al. (2003); Venkatesh et al. (2012)
Effort expectancy (EE)	EE01: I can easily become proficient in using AI tools. EE02: I find it easy to use AI tools for knowledge management. EE03: The user interface of AI tools is friendly. EE04: Learning how to handle and operate AI tools is easy for me.	Venkatesh et al. (2003); Venkatesh et al. (2012)
Behavioral intention to use (BIU)	BI01: I am willing to recommend others to use AI tools. BI02: I plan to use AI tools as learning tools. BI03: I would be interested in participating in teaching activities involving AI tools.	Duong et al. (2023); Venkatesh et al. (2003); Venkatesh et al. (2012)

	BI04: I am interested in using AI tools more frequently in the future.

Note. AI = artificial intelligence.