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Effect of AI Technology Acceptance and Use on Behavioral Intentions and Career Adaptability

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Abstract
This study explores how UTAUT2 factors influence college students' intentions to adopt AI and their career adaptability. Survey data from 327 students show that Performance Expectancy, Hedonic Motivation, and Habit significantly impact AI adoption, while Effort Expectancy, Facilitating Conditions, Hedonic Motivation, Price Value, and Habit influence career adaptability. The findings suggest that fostering positive attitudes toward AI is essential. To prepare students for an AI-driven workforce, the study recommends integrating AI into curricula, providing necessary resources, and promoting collaborative learning to support skill development and adaptability in a rapidly evolving technological landscape.

Keywords: Artificial Intelligence (AI), UTAUT2, Behavioral Intentions, Career Adaptability

1.0 Introduction

1.1 Research Background

Artificial intelligence (AI) is shaking things up in almost every industry. With technology advancing so quickly, the kinds of skills employers are looking for are changing too. As companies bring more AI into their operations, they need workers who can keep up (Rashid & Kausik, 2024). For students about to start their careers, it's essential to build the skills that will help them adjust to these new demands.

One way to think about how people decide to use new technology is through the UTAUT2 model, which was introduced by Venkatesh and his team in 2012. It looks at a few things: how useful a technology is, how easy it is to use, and how much other people influence your decisions. Several factors can influence an individual's decision to engage with technologies such as AI (Darioshi & Lahav, 2021). To succeed in a changing job market, students must grasp how these factors affect real-world situations. This understanding can help them adjust to new work environments and be more open to using technologies like AI in their careers (Cortez et al., 2024).

Career adaptability—the capacity to adjust to changes in the workplace—has become increasingly critical as AI transforms job roles. Additionally, students' willingness to adopt AI technologies is a significant predictor of their ability to effectively use these tools, which, in turn, can impact their capacity to capitalize on emerging career opportunities (Rashid & Kausik, 2024).

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This study investigates the factors that influence college students' behavioral intentions and career adaptability, offering valuable insights to inform strategies that can better prepare students for a technology-driven job market.

1.2 Research Objectives

This study has two main goals. The first is to understand how the factors in the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) affect college students' intentions to adopt AI technologies. Specifically, it looks at how things like performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and habit impact students' decisions to use AI tools and applications (Venkatesh et al., 2012).

The second part of this study examines how factors derived from the UTAUT2 model influence students' behavioral intentions and career adaptability. It focuses on understanding students' perceptions of AI—specifically, whether they perceive it as useful and easy to use—and how these perceptions affect their ability to adapt to emerging job demands and advance in their careers (Decius et al., 2013). The study aims to provide insights into how the adoption of new technologies can enhance career flexibility and inform the development of educational strategies and policies.

1.3 Research Questions

This study focuses on these main questions:

RQ1: What factors influence college students' behavioral intentions to adopt AI technologies?

RQ2: How are these factors related to students' ability to adapt in terms of career adaptability?

These questions will help explore how students' openness to technology impacts their readiness to use AI and their ability to adjust to changing job opportunities.

2.0 Literature Review

2.1 The Extended Unified Theory of Acceptance and Use of Technology (UTAUT2)

The UTAUT2 model is a key framework for understanding the factors that influence technology acceptance, especially in educational settings (Cortez et al., 2024). Each element in the model plays an important role in shaping how people use and decide to adopt technology:

Performance Expectancy (PE) refers to how much people believe that using a technology will improve their performance. In education setting, students who see AI tools as helpful for improving their learning outcomes are more likely to use them. Previous studies have shown that performance expectancy is a strong predictor of technology adoption, making it a crucial factor in education (Cortez et al., 2024).

Effort Expectancy (EE) is about how easy a technology is to use. When students find a technology intuitive and simple, they're more likely to adopt it. Research has demonstrated that making technology easy to use increases students' willingness to engage with it, helping them succeed in their studies (Davis, 1989; Venkatesh et al., 2003).

Social Influence (SI) involves how much students feel that important people in their lives—like friends, family, and teachers—encourage them to adopt a technology (Venkatesh et al., 2012). Peer support can be a powerful motivator, boosting students' confidence and making them more likely to explore new technologies.

Facilitating Conditions (FC) refer to the support and resources that make it easier for people to use technology. This includes access to infrastructure, training, and technical help. When students feel they have the necessary resources, they are more likely to use technology. For this reason, it's essential for schools to provide the tools and support that students need to take full advantage of new technologies (Venkatesh et al., 2012).

Hedonic Motivation (HM) is about the enjoyment people get from using technology. When students find AI tools fun or interesting, they're more likely to use them. In educational settings, keeping students engaged is key to improving learning outcomes (Cortez et al., 2024).

Price Value (PV) relates to how students weigh the costs of using technology against its benefits. Financial concerns can play a big role in whether or not students choose to adopt a new technology, so it's important that the perceived value of the technology justifies its cost (Venkatesh et al., 2012).

Habit (HT) is the degree to which using technology becomes automatic over time. As students get used to using certain tools, they are more likely to continue using them, especially if these tools have already become part of their routine (Venkatesh et al., 2012).

2.2 Behavioral Intention

Cortez et al. (2024) describe behavioral intention (BI) as a key factor in predicting whether people will actually use technology, reflecting how likely they are to adopt a behavior—in this case, using AI technologies. Many studies have shown a strong link between positive views of technology, shaped by factors like performance expectancy and effort expectancy, and the intention to use it (Davis, 1989; Venkatesh et al., 2003, 2012). Understanding what influences these intentions is crucial for creating a workforce that not only knows how to use technology but is also ready to adapt to the continuous changes in their fields (Venkatesh et al., 2012).

2.3 Career Adaptability

Career adaptability is a psychosocial construct that reflects individuals' resources for managing career tasks and challenges, including those relevant to students as they prepare for their future careers (Zacher, 2014). Savickas (1997) emphasizes that career adaptability involves four key components: concern, control, curiosity, and confidence. As technological advancements continue to reshape job roles, students must cultivate these qualities to navigate change and achieve success (Chanda et al., 2024).

Studies show that people who are good at adapting to changes in their careers tend to take more initiative, whether that means finding new learning opportunities or building connections with others (Savickas & Porfeli, 2012). This is especially important with the rise of AI, since the ability to pick up new skills and stay on top of technology can really affect job prospects and career growth (Rashid & Kausik, 2024).

2.4 Connections Between Research Constructs

The way UTAUT2 factors, career adaptability, and students' intentions to adopt AI technologies interact is important, though it's not always straightforward. Research has shown that when students see AI technologies as both useful and easy to use, they're more likely to want to use them (Ayanwale & Ndlovu, 2024). This interest can help students become more adaptable in their careers by motivating them to learn new skills as technology evolves (Haleem, et al., 2022). To better understand how adopting new technologies influences their preparedness for the job market, it's important to explore these connections further.

Building on earlier research, this study proposes the following hypotheses:

H1: There is a significant relationship between the UTAUT2 factors and college students' behavioral intentions to use AI technologies.
H2: There is a significant relationship between the UTAUT2 factors and career adaptability among college students.
H3: The UTAUT2 factors collectively predict college students' behavioral intentions to use AI technologies.
H4: The UTAUT2 factors collectively predict career adaptability among college students.

These hypotheses will guide the research into how factors like Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Hedonic Motivation, Price Value, and Habit—along with other relevant influences—affect both students' intentions to adopt AI and their career adaptability.

3.0 Methodology

This study uses a quantitative approach, collecting data through a structured survey distributed to college students. A cross-sectional method is employed to examine the relationships between variables in 2024. This approach offers a detailed overview of college undergraduates' views and behavioral intentions related to emerging technologies, providing insight into their career adaptability and future plans.

3.1 Participants

The study included 327 college undergraduates from different academic majors in Taiwan. This group is important because it represents a generation that is comfortable with technology and familiar with AI. The sample had a fairly balanced gender distribution, with 39.4% male and 60.6% female counterparts. Participants were chosen to ensure a diverse representation of the student population.

3.2 Measures

The survey is divided into four sections. The first section collects basic demographic information, such as gender and academic major. The second section uses a seven-point Likert scale to gather students' views on factors like performance expectancy (PE), effort expectancy (EE), social influence (SI), facilitating conditions (FC), hedonic motivation (HM), price value (PV), and habit (HT) (Venkatesh et al., 2012). The third section focuses on students' intentions (BI), and the final section looks at career adaptability (CA) using a scale by Savickas and Porfeli (2012) to ensure the survey is reliable and valid.

3.3 Data Analysis

Data analysis for this study was conducted using SPSS. Initially, descriptive statistics were computed to provide an overview of the data. Subsequently, the assumptions of normality were evaluated by analyzing the skewness and kurtosis values of the research measures. To evaluate the item-level reliability of the scales, Cronbach's alpha was applied. The study employed correlation analysis to explore the relationships between the UTAUT2 constructs, behavioral intention (BI), and career adaptability (CA), uncovering valuable insights into technology acceptance, behavioral intentions, and career adaptability. Additionally, multiple regression analysis was used to identify the main predictors of both BI and CA. All statistical tests were two-tailed, using a significance threshold of $p < 0.05$.

4.0 Findings

The college student participants had mean (SD) scores of 5.39 (1.179) for Performance Expectancy (PE), 5.46 (1.165) for Effort Expectancy (EE), 4.82 (1.330) for Social Influence (SI), 5.35 (1.112) for Facilitating Conditions (FC), 5.25 (1.218) for Hedonic Motivation (HM), 4.97 (1.217) for Price Value (PV), 4.18 (1.491) for Habit (HT), 5.09 (1.307) for Behavioral Intentions (BI), and 5.48 (1.000) for Career Adaptability (CA). Additionally, the skewness values varied between -0.065 and -0.914, while the kurtosis values ranged from

0.732 to 1.086. These values indicate that UTAUT2 constructs, BI, and CA are normally distributed, based on the guidelines set forth by Muthèn and Kaplan (1985).

Reliability is essential in research because it ensures that the tools used to collect data produce consistent and trustworthy results. In this study, the reliability of the scales is evaluated using Cronbach's alpha coefficients. For this study, the reliability of the scales was assessed using Cronbach's alpha coefficients. The values for each construct were as follows: Performance Expectancy (PE) = 0.945, Effort Expectancy (EE) = 0.960, Social Influence (SI) = 0.663, Facilitating Conditions (FC) = 0.932, Hedonic Motivation (HM) = 0.893, Price Value (PV) = 0.949, Habit (HT) = 0.932, Behavioral Intentions (BI) = 0.909, and Career Adaptability (CA) = 0.959. The reliability of the scales used in this study was confirmed, with all Cronbach's alpha values above the 0.60 threshold, which indicates good consistency (Hajjar, 2018).

Looking at the bivariate correlations, all of the UTAUT2 factors showed positive relationships with both Behavioral Intentions (BI) and Career Adaptability (CA). Among these, Performance Expectancy (PE) had the strongest link to BI ($r = 0.768$, $p < 0.001$), followed by Effort Expectancy (EE) ($r = 0.698$, $p < 0.001$) and Hedonic Motivation (HM) ($r = 0.747$, $p < 0.001$). Other factors, such as Social Influence (SI) (r = 0.673, $p < 0.001$), Facilitating Conditions (FC) ($r = 0.684$, $p < 0.001$), Price Value (PV) ($r = 0.607$, $p < 0.001$), and Habit (HT) ($r = 0.725$, $p < 0.001$), also showed positive correlations with BI.

Similar positive correlations were observed between Career Adaptability (CA) and the UTAUT2 factors. Performance Expectancy (PE) ($r = 0.636$, $p < 0.001$) and Effort Expectancy (EE) ($r = 0.696$, $p < 0.001$) were strongly linked to CA, as well as Social Influence (SI) ($r = 0.432$, $p < 0.001$), Facilitating Conditions (FC) ($r = 0.693$, $p < 0.001$), and Hedonic Motivation (HM) ($r = 0.637$, $p < 0.001$). Price Value (PV) ($r = 0.512$, $p < 0.001$) and Habit (HT) ($r = 0.268$, $p < 0.001$) also showed significant, though weaker, correlations with CA.

These findings suggest that higher levels of UTAUT2 constructs are associated with increased AI behavioral intentions and the ability of college students to adapt to their careers. Additionally, the magnitude of the correlation between UTAUT2 constructs and behavioral intentions was greater than that between UTAUT2 constructs and career adaptability. Thus, Hypotheses 1 and 2 were supported.

Table 1 displays the outcomes of the multiple regression analysis examining the relationship between UTAUT2 constructs and AI behavioral intentions. The analysis reveals that the UTAUT2 constructs account for 76.4% of the total variance in behavioral intentions ($F(7, 319) = 147.86$, $p = 0.001$). Variance inflation factor values range from 1.811 to 5.145, suggesting the absence of multicollinearity concerns between the research variables.

Among the predictors, Performance Expectancy (PE) emerged as significant ($\beta = 0.334$, $t = 5.727$, $p = 0.000$, 95% CI [0.243, 0.498]). Hedonic Motivation (HM) was also identified as an important determinant ($\beta = 0.248$, $t = 4.912$, $p = 0.000$, 95% CI [0.159, 0.372]), as was Habit (HT) ($\beta = 0.365$, $t = 9.972$, $p = 0.000$, 95% CI [0.257, 0.383]). Consequently, partial support was found for Hypothesis 3.

Table 1. Multiple Regression Results for UTAUT2 Constructs and AI Behavioral Intentions

Predictor	Unstandardized Coefficients		Standardized Coefficients	*t*	*p*	95%CI for B		Collinearity Statistics	
	B	S. E.	Beta			Lower Bound	Upper Bound	Tolerance	VIF
Constant	-.074	.186		-.399	.690	-.440	.292		
PE	.371	.065	.334	5.727	.000	.243	.498	.217	4.612
EE	-.006	.069	-.005	-.085	.932	-.142	.130	.194	5.145
SI	.065	.041	.067	1.599	.111	-.015	.146	.425	2.355
FC	-.011	.067	-.009	-.160	.873	-.143	.121	.227	4.412
HM	.266	.054	.248	4.912	.000	.159	.372	.291	3.439
PV	.042	.043	.039	.972	.332	-.043	.127	.459	2.177
HT	.320	.032	.365	9.972	.000	.257	.383	.552	1.811
R^2	76.4%								
F	147.86*								

PE= performance expectancy; EE=effort expectancy; SI= social influence; FC= facilitating conditions; HM= hedonic motivation; PV= price value; HT=habit. *$p<0.05$.

A summary of the multiple regression analysis results is shown in Table 2 concerning UTAUT2 constructs and career adaptability among college students. The variance inflation factor values ranged from 1.811 to 5.145, further confirming the absence of multicollinearity among the variables. The model accounted for 56.2% of the overall variance ($F(7, 319) = 58.449$, $p = 0.000$).

In this analysis, Effort Expectancy (EE) was found to demonstrate a substantial predictor ($\beta = 0.320$, $t = 3.810$, $p = 0.000$, 95% CI [0.133, 0.417]). Facilitating Conditions (FC) also emerged as a significant determinant ($\beta = 0.292$, $t = 3.747$, $p = 0.000$, 95% CI [0.125, 0.400]). Additionally, Hedonic Motivation (HM) ($\beta = 0.152$, $t = 2.219$, $p = 0.027$, 95% CI [0.014, 0.236]), Price Value (PV) ($\beta = 0.116$, $t = 2.118$, $p = 0.035$, 95% CI [0.007, 0.184]), and Habit (HT) ($\beta = 0.164$, $t = -3.280$, $p = 0.001$, 95% CI [-0.176, -0.044]) were also significant predictors. Therefore, Hypothesis 4 was partially supported.

Table 2. Multiple Regression Results for UTAUT2 Constructs and Career Adaptability

Predictor	Unstandardized Coefficients		Standardized Coefficients	*t*	*p*	95%CI for B		Collinearity Statistics	
	B	S. E.	Beta			Lower Bound	Upper Bound	Tolerance	VIF

Constant	1.767	.194		9.107	.000	1.385	2.148		
PE	.074	.068	.087	1.097	.273	-.059	.207	.217	4.612
EE	.275	.072	.320	3.810	.000	.133	.417	.194	5.145
SI	-.055	.043	-.073	-1.277	.203	-.139	.030	.425	2.355
FC	.262	.070	.292	3.747	.000	.125	.400	.227	4.412
HM	.125	.056	.152	2.219	.027	.014	.236	.291	3.439
PV	.095	.045	.116	2.118	.035	.007	.184	.459	2.177
HT	-.110	.033	-.164	-3.280	.001	-.176	-.044	.552	1.811
R^2	56.2%								
F	58.449*								

PE= performance expectancy; EE=effort expectancy; SI= social influence; FC= facilitating conditions; HM= hedonic motivation; PV= price value; HT=habit. $^*p<0.05$.

5.0 Discussion

This study investigated the factors influencing college students'' willingness to adopt AI technologies and their adaptability to career changes, using the Extended Unified Theory of Acceptance and Use of Technology (UTAUT2). Findings revealed that Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), Hedonic Motivation (HM), Price Value (PV), and Habit (HT) were significant determinants of students' attitudes toward AI. Regression analyses identified PE, HM, and HT as key predictors of behavioral intention to use AI, while EE, FC, HM, PV, and HT significantly influenced career adaptability.

These results underscore the importance of UTAUT2 constructs in shaping students' readiness to engage with AI and navigate a rapidly evolving job market. In particular, students' perceptions of AI's usefulness, ease of use, and enjoyment are critical for fostering both adoption and adaptability. Educational institutions should therefore focus on enhancing these perceptions to support students' technological competence and career flexibility.

Overall, the findings provide valuable insights into how UTAUT2 factors contribute to AI adoption and career adaptability. They highlight the potential impact of supportive, engaging learning environments in preparing students for technology-driven careers. To advance this field, future research should adopt longitudinal designs, involve more diverse and representative samples, and conduct cross-cultural comparisons. These approaches would offer deeper insights into how these factors evolve over time and across contexts, enabling more targeted educational strategies.

6.0 Conclusion & Recommendations

This study confirms that UTAUT2 constructs significantly influence college students' intentions to adopt AI and their career adaptability. PE, HM, and HT emerged as key predictors of AI adoption, while EE, FC, HM, PV, and HT were significant for career adaptability. These results suggest that promoting positive attitudes toward AI and supporting career adaptability are essential for preparing students for a fast-changing technological landscape (Jivtode, 2024; Vieriu & Petrea, 2025).

Based on the findings, several recommendations are proposed. Educational institutions should incorporate AI into curricula, emphasizing practical, user-friendly applications. Providing access to tools, training, and mentorship will foster a supportive environment for adoption and growth. Facilitating peer collaboration can strengthen social influence, while interactive, engaging learning—such as simulations and real-world tasks—can enhance hedonic motivation and interest in AI.

Future studies should track changes in student attitudes and adaptability over time and explore the role of demographic factors in shaping AI engagement. Policymakers are encouraged to support lifelong learning initiatives and workforce development programs that promote adaptability in AI-driven industries.

This study is not without limitations. The sample was limited to university students in Taiwan, which may constrain generalizability. Reliance on self-reported data introduces potential biases, and the cross-sectional design limits causal inference. To address these issues, future research should employ longitudinal methods, include more diverse populations, and use objective measures. Doing so will deepen understanding of the drivers behind AI adoption and career adaptability, informing more effective educational and policy interventions for an AI-integrated future.

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Paper Contribution to Related Field of Study

This study investigates how educational institutions can better equip students for a job market increasingly influenced by technology. As AI adoption grows, understanding the factors that affect students' use of these technologies is crucial. The findings offer valuable insights for colleges to design programs and support systems that foster adaptability, thereby preparing students for future career challenges. Additionally, the research highlights how focusing on key skills and the right mindset can enhance students' ability to adapt to evolving career demands. By examining the relationship between the UTAUT2 model, technology adoption behaviors, and career adaptability, this study contributes to the ongoing discussion about the role of technology in education and how we can better prepare students for an AI-driven future.

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