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Examining generative artificial intelligence adoption in academia: a UTAUT perspective

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Abstract

Artificial Intelligence (AI) technology has seen rapid growth in higher education institutions over the past few years, prompting questions into the usage and underlying acceptance factors of these computer systems. This study investigates characteristics of student adoption within generative AI tools, also known as chatbots, utilizing the previously established Unified Theory of Acceptance and Use of Technology (UTAUT) model. A partial least squares regression (PLSR) model is deployed using data collected from a survey of 74 respondents to examine which UTAUT constructs are influencing undergraduate usage behavior of generative AI tools. Understanding factors of AI acceptance is of value to educators as they can design classroom interventions for adoption to enhance academic and professional potential within student populations, especially delayed users. In addition, insights developed into attributes of adoption may be of use to understand generative AI acceptance under the UTAUT framework. Results indicate that productivity gains, mentor perspective, peer usage, and broadness of tasks performed drive generative AI adoption in academic settings. Additionally, empirical results found that demographics, such as gender and age, are not factors influencing generative AI use. Future research is suggested to compare results found in this study with the Value-based Adoption Model (VAM) to corroborate characteristics of student adoption in a marginal benefit vs marginal cost trade-off setting.

Keywords: generative artificial intelligence, technology adoption, UTAUT, undergraduate students, education

Introduction

The use of generative AI products, known as chatbots, has rapidly grown in academia since OpenAI released Chat Generative Pre-Trained Transformer (ChatGPT) in November 2022 (Kocoń et al., 2023). Generative AI tools are large language models that provide detailed answers from human-interacted input using statistical methods and machine learning techniques (Roumeliotis & Tselikas, 2023). AI development and improvement show no signs of slowing down as more human interaction within the system allows reinforcement learning to occur within the system, making the outputs more efficient (Fui-Hoon Nah et al., 2023; Ibrahim et al., 2023; Whalen & Mouza, 2023). These systems will continue to improve as usage increases, suggesting that these tools are here to stay long-term.

The generative AI field has become prevalent among students in higher education institutions and individuals in the labor force. Awareness of AI's assistance in everyday life has significantly increased, especially among academic students (Rasul et al., 2023). Despite ethical concerns of use in educational settings (Baidoo-Anu & Ansah, 2023; Walton et al., 2023), generative AI skills are becoming increasingly popular in professional settings post-graduation (Grassini, 2023). Thus, it is imperative to provide equitable outcomes for students across all disciplines to develop the required skills for thriving in an AI-dominated future. In addition to positive labor market outcomes, research has indicated that AI tools positively impact learning quality in academic settings (Huang et al., 2021). Thus, developing AI skills allows students to enhance their academic and professional potential.

The main goal of this study is to understand the motivating factors driving students' adoption of AI tools in higher education institutions. Insights into how and why students use AI tools allow educators to tailor curricula promoting effective and responsible use for enhancing students' academic and professional potential. This study uses the UTAUT framework, described by Venkatesh et al. (2003) as empirically the most productive information technology acceptance model, to determine characteristics of student adoption amongst students at a small business school in New England.

The results are useful to educators in developing AI literacy skills among their students and bridge the gap between students naturally adopting AI technology and students not adopting the system. Instructors may gain awareness of different factors driving behavioral intention and usage through the UTAUT model. UTAUT is based on constructs of performance expectancy, effort expectancy, social influence, and facilitating conditions. Gender, age, and experience are moderators of the four primary constructs within the model. See Figure 1.

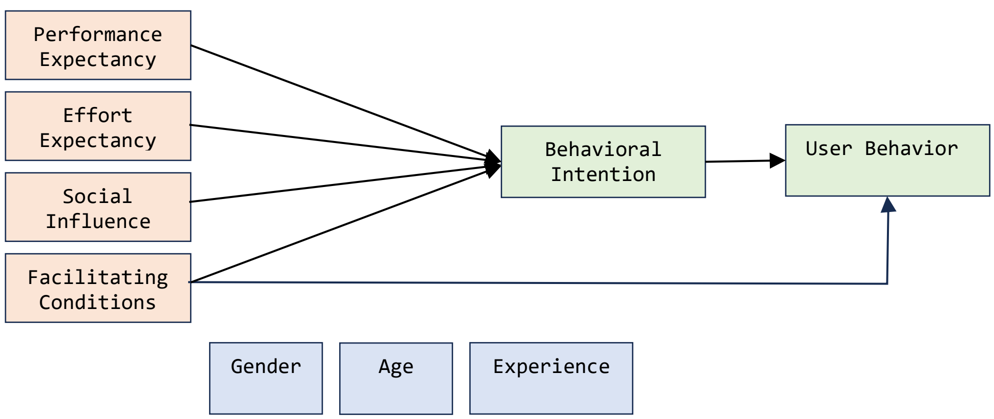

Figure 1: Components of the UTAUT model.

Performance expectancy describes an individual's belief that AI technology will improve job performance. Effort expectancy denotes simplicity related to using the system. Social influence is the belief that important individuals to the respondent indicate that AI technology use is crucial. Facilitating conditions are defined as the respondent's perception that an organization supports using the technology. With insights into characteristics impacting adoption, educators can adapt teaching to incorporate constructs driving usage into their lesson plans for increased technology acceptance.

Yu and Guo (2023) describe a need to develop a mechanism to achieve optimal student learning outcomes regarding AI tools in academia. This study examines survey results related to generative AI usage among college students to develop an efficient learning model. The well-established UTAUT theory for technology adoption provides a framework for educators to create learning scenarios to bridge the gap between student's current knowledge and the skills they need to learn, enhance their academic potential, and ultimately increase their likelihood of success in the labor market.

Background and literature review

Research by Kasneci et al. (2023) states the need for a clear strategy within educational settings to achieve favorable learning outcomes with AI tools. This need is exacerbated by the recent adoption of generative AI tools within academia (Wong, 2024). The demand for a clear strategy is further underlined by the controversial nature of AI tools in education, as the benefits to students are often examined against the potential costs (Eke, 2023). Although AI systems could significantly accelerate innovation, potentially leading to breakthroughs across many different disciplines (Kwak et al., 2023; Van Dis et al., 2023; Vanjani & Posey, 2023), there also exists concern for lack of creative development and academic dishonesty amongst undergraduates (Baidoo-Anu & Ansah, 2023).

Understanding undergraduate adoption is essential, as AI tools can influence academic and professional outcomes (Atlas, 2023). According to Steele (2023), generative AI systems develop critical thinking skills amongst students as they question and critique the given output. Critical thinking development assists in creating efficient learning outcomes across many courses (Hafeez, 2021; McMillan, 1987). Regarding labor market opportunity, research indicates a positive and significant association between AI usage and firm productivity using empirical data (Czarnitzki et al., 2023; Yu & Qi, 2024). Employers seek knowledgeable workers familiar with AI tools to enhance productivity and drive profit but find employees lack the necessary skills (Al Naqbi et al., 2024; Lozie et al., 2024). Students developing AI skills in college enhance their academic learning and increase their competitiveness in the labor market post-education.

All students must develop generative AI skills to close the technical skills gap found by Mentzer et al. (2024), as research conducted by Noy and Zhang (2023) reveals that using AI tools benefits individuals with weaker technological skills. The individuals with lower abilities were more productive and efficient compared to the randomly selected group not assigned to use ChatGPT. Brynjolfsson et al. (2023) found significant heterogeneity related to generative AI tools, as worker productivity was boosted by 14%, on average, but increased by 34% for novice and low-skilled workers. This increased productivity is a proxy for non-adopters to "catch up" with their tech-savvy peers. Thus, students who are less inclined to adopt AI tools should be included in policy intervention to assist them in reaching their full potential. For these students, not adopting AI technology may further increase inequality (Bansal et al., 2023).

According to Venkatesh et al. (2003), the originator of the UTAUT model, the framework provides a useful tool for leaders to understand the influences of technology acceptance to increase usage amongst natives less inclined to adopt the technology. Additional research by Venkatesh (2022) provides theoretical support for the UTAUT model in studying the adoption of AI tools and thus provides a foundation for the researchers to use the model over other widely received models, such as the Technology Acceptance Model (TAM) (Davis, 1989) and Value-based Adoption Model (VAM) (Kim et al., 2007).

Main contribution of the paper

The main contribution of this paper is to add to the growing literature examining technology acceptance in academia related to generative AI tools. The technology acceptance model (TAM) has been confirmed concerning AI (Saif et al., 2024). Research by Strzelecki (2023), most similar to this paper, found that the UTAUT model generally aligns with ChatGPT adoption in Poland. This research utilizes additional constructs included by Agarwal and Prasad (1998); thus, it is not an exact use of the original UTAUT framework described by Venkatesh et al. (2003).

Previous literature regarding ChatGPT and generative AI tools has not examined student adoption strictly using the constructs of the prominent unified UTAUT model with a United States target population. In total, 174 research papers have utilized the UTAUT framework to analyze a wide range of technologies (Williams et al., 2015). The investigation performed in this paper examines results related to generative AI utilizing a proven mechanism for technology acceptance to provide insights into what factors are driving adoption within these systems in higher education.

Methodology

Survey Instrument

To understand how students utilize artificial intelligence tools, namely ChatGPT and Google Gemini (formerly known as Bard), students were asked to complete a survey highlighting the motivating factors of AI use in their academic and personal lives. The survey began with two demographic-based questions to understand the survey respondents' gender and age. After accounting for experience with the technology and the corresponding frequency, eight subsequent questions were asked about the respondents' use of AI tools utilizing the UTAUT constructs (Venkatesh et al., 2003). The survey questions aimed to understand the interplay of the respondents' demographics, moderators, and their perspectives on using AI. The researchers use the UTAUT framework as strict inputs for modeling a direct effect on the intention to use generative AI tools. This study does not examine Interactions between model inputs but may provide additional enlightenment. The survey questions are reported below in Table 1, on page 5.

Partial least squares regression (PLSR) model

PLSR is utilized to explore constructs that load into latent components by maximizing covariance with the response variable of use behavior. Groups of constructs comprising the components interest educators as they denote similar characteristics driving the adoption of AI use. Conversely, characteristics that do not load into components can be said to lack association with adoption. The direction of each component does not have any interpretation for the model deployed during this study, as the factor response of the target variable is not ordinal. The absolute value of each construct is of interest as this denotes what technology adoption competencies group together to create latent components for better understanding factors of generative AI adoption.

Partial least squares regression (PLSR), introduced by Wold (1975), is a parametric technique to account for high dimensional data where the number of features is greater than the number of observations or when there exists multicollinearity amongst predictors. Although the sample in this study exhibits neither of these issues, PLSR is of value to educators in that insights about similar groups of technology adoption constructs are allowed while predicting use behavior. In addition, research by Venkatesh et al. (2003) uses PLSR in creating the UTAUT model. Thus, this paper's researchers thought it appropriate to examine the sample in the same light.

The PLSR algorithm utilizes an approach like the unsupervised Principal Components Analysis (PCA) that creates orthogonal latent variables, or components, comprised of features grouped by similarities. PLSR, however, is a supervised method that considers variance in the target variable. Instead of maximizing predictor variance as in PCA, PLSR creates components, or directions, by their magnitude of covariance with the target variable while retaining the most possible amount of information in the original variables.

A series of simple linear regression models are then sequentially performed stepwise using the orthogonally created latent variables to find an optimal hyperplane that maximizes predictor covariance with the target variable. The result is a supervised dimension reduction approach that is more appropriate for predictive goals than traditional PCA methods that are unsupervised and do not use information in the response to group features into components.

Table 1: Survey Questions

Examining Students Use of Artificial Intelligence in Education		
UTAUT Construct	**Question Asked**	**Response Items**
Use Behavior (target variable)	Which task the respondent most frequently uses AI tools for.	1. Respondent does not use AI tools. 2. To solve math problems. 3. To generate code. 4. To summarize code. 5. To summarize text. 6. To generate visuals. 7. To better understand a concept or theory. 8. Other
Demographics	The respondents preferred gender.	1. Male 2. Female 3. Other
Demographics	The respondents age.	Select age (18 – 27+)
Experience	The respondents experience using AI tools, such as ChatGPT.	1. Have not used AI tools. 2. Have just started using AI tools within the last 30 days. 3. Have been using AI tools for less than 6 months but more than a month. 4. Have been using AI tools for less than a year but more than 6 months. 5. Have been using AI tools for more than a year.
Frequency of Experience	How often does the respondent uses AI tools such as ChatGPT.	1. Never 2. Rarely 3. Monthly 4. Weekly 5. Daily
Behavioral Intention	The way in which the respondent intends to use AI tools.	1. Respondent does not use AI tools. 2. Analyze the steps that reach a given output. 3. Evaluate the given output for accuracy. 4. Accept the given output without much assessment.
Performance Expectancy 1	Using AI tools enables me to accomplish tasks more quickly.	1. Strongly disagree. 2. Disagree. 3. Somewhat disagree. 4. Neither agree nor disagree. 5. Somewhat agree. 6. Agree 7. Strongly agree.
Performance Expectancy 2	Using AI tools increases my chances of receiving a higher grade or landing an internship/job.	Same 7-Point Scale as above.
Effort Expectancy 1	I find it easy to get AI tools to do what I want them to do.	Same 7-Point Scale as above.
Effort Expectancy 2	Using AI tools takes too much time performing prompt input(s).	Same 7-Point Scale as above.
Social Influence 1	Individuals that are important to me believe that I should use AI tools (This may be the respondent's parent, professor, or mentor.)	Same 7-Point Scale as above.

Social Influence 2	I use AI tools because of the proportion of students/peers that use it.	Same 7-Point Scale as above.
Facilitating Conditions 1	Using AI tools is compatible with all aspects of my work.	Same 7-Point Scale as above.
Facilitating Conditions 2	Instruction was given to me concerning AI use.	Same 7-Point Scale as above.

$$\hat{\beta}_{k-1,j} = \frac{\mathrm{cov}\left(\mathbf{x}_j^{(k-1)}, \mathcal{Y}^{(k-1)}\right)}{var\ (\mathbf{x}_j^{(k-1)})}$$

In the first step of PLSR, exhibited above (Izenman, 2009), components are derived from an iterative series of simple linear regressions where $\mathcal{Y}^{(k-1)}$ is regressed on $\mathbf{x}_j^{(k-1)}$. The first PLSR component, Z, is a vector created by the beta 1 parameter estimates from a simple linear regression of the response variable on each independent variable. Where the weighted average Z is computed as a predictor of y (Izenman, 2009):

$$\mathbf{z}_k \propto \sum_{j=1}^{r} \mathrm{cov}\left(\mathbf{x}_j^{(k-1)}, \mathcal{Y}^{(k-1)}\right) \cdot \mathbf{x}_j^{(k-1)}$$

The independent variables with higher correlation are given more weight in the direction of the first component (Hastie et al., 2009). The target variable is then regressed on this newly created vector, Z, which utilizes the correlation weights, or parameter estimate, in the original OLS regression (Izenman, 2009) as shown by:

$$\hat{\theta}_k = \frac{\mathrm{cov}\left(\mathbf{z}_k, \mathcal{Y}^{(k-1)}\right)}{var\ (\mathbf{z}_k)}$$

thus, the residual vector becomes $\mathcal{Y}^{(k)} = \mathcal{Y}^{(k-1)} - \hat{\theta}_k \mathbf{z}_k$

To orthogonalize the second component, variation that has already been explained in the first component is removed from the original variables not comprising the first component. To do this, the value of each independent variable is then replaced by the residual, the difference between predicted and observed values, from simple linear regression performed on the first component, Z (Bair et al., 2006), denoted below (Izenman, 2009):

$$\hat{\phi}_{kj} = \frac{\mathrm{cov}\left(\mathbf{z}_k, \mathbf{x}_j^{(k-1)}\right)}{var\ (\mathbf{z}_k)}$$

Whereas the residual vector equals $\mathbf{x}_j^{(k)} = \mathbf{x}_j^{(k-1)} - \hat{\phi}_{kj} \mathbf{z}_k$

This creates orthogonalization with respect to Z for the second component, W, as the variation explained in the target is removed for the second iteration. The second component is then created like the first but using the residual data as observations for each feature instead of the original ones. The created third component uses residual data from the 2^{nd} component, W, and the process continues until the tuning parameter, the number of components, is reached (Hastie et al., 2009). This iteration of replacing original observations with residuals of component creation allows orthogonalization to be achieved.

As PLSR requires a tuning parameter, the number of components to create before the final model selection and many different values of t, the number of components to create, are explored to determine the most effective input for final model selection. The number of components that minimize RMSE is selected through the utilization of 10-fold cross-validation techniques. According to Izenman (2009), the process stops when:

$$\sum_{j=1}^{r} \operatorname{var}\left(\mathbf{x}_j^{(k)}\right) = 0$$

thus, creating the final PLSR model form of

$$\hat{\mathcal{Y}}_{\text{plsr}}^{(t)} = \bar{y}\mathbf{1}_n + \sum_{k=1}^{t} \hat{\theta}_k \mathbf{z}_k$$

Results/Findings

The descriptive stats in Table 2 denote that 58 percent of observations are male, while the average age is approximately 19.5 years old. The UTAUT framework constructs of Performance 1, Performance 2, Effort 1, Effort 2, Social 1, Social 2, Facilitating 1, and Facilitating 2 are average Likert scale responses as reported in Table 1.

Table 2: Descriptive statistics of survey results

	n	mean	sd	min	max
Gender	74	0.581	0.497	0	1
Age	74	19.397	1.244	18	23
Experience	74	3.392	1.280	1	5
Behavioral Intention	74	3.081	0.990	1	4
Performance 1	74	5.649	1.548	1	7
Performance 2	74	4.662	1.690	1	7
Effort 1	74	5.176	1.388	1	7
Effort 2	74	3.595	1.525	1	7
Social 1	74	4.311	1.679	1	7
Social 2	74	3.635	1.962	1	7
Facilitating 1	74	3.959	1.846	1	7
Facilitating 2	74	4.378	1.870	1	7
Use Behavior	74	4.459	1.903	1	7

Students reported the highest agreement levels with Performance Expectancy 1, denoting that AI tools enable tasks to be completed more quickly. Also high in agreement is Effort Expectancy 1, reporting that it is easy for students to get AI tools to do what they want. Figure 2 below displays the average self-reported constructs with standard error bars included.

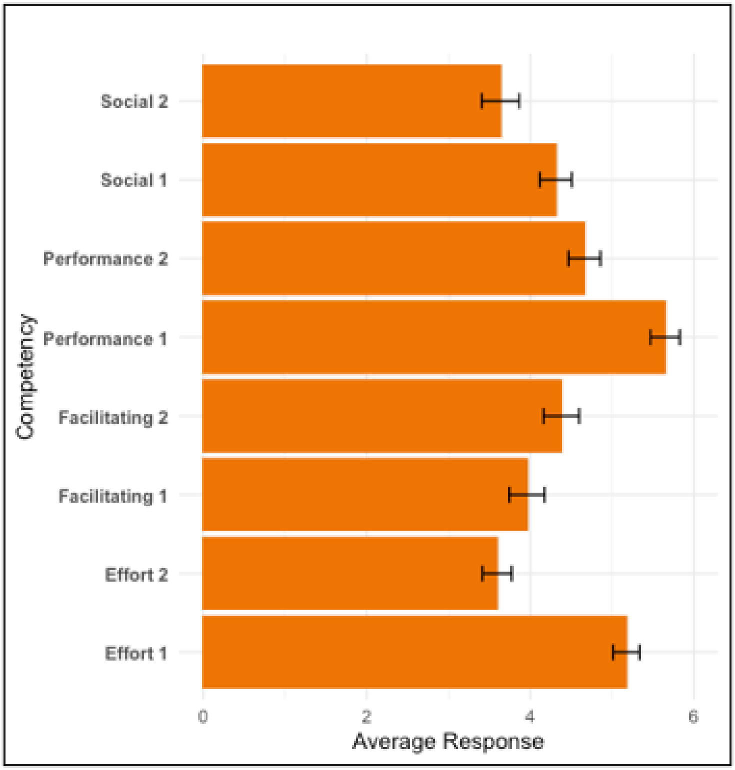

Figure 2: Average UTAUT competencies with standard errors

As one of the primary goals of PLSR is to account for multicollinear data, a correlation matrix of variables is showcased below in Figure 3. Each cell contains a correlation coefficient of pairwise variables. Correlation quantifies the direction and strength of the linear relationship between variables. The color gradient denotes the breadth of the correlation, with darker orange indicating a stronger correlation.

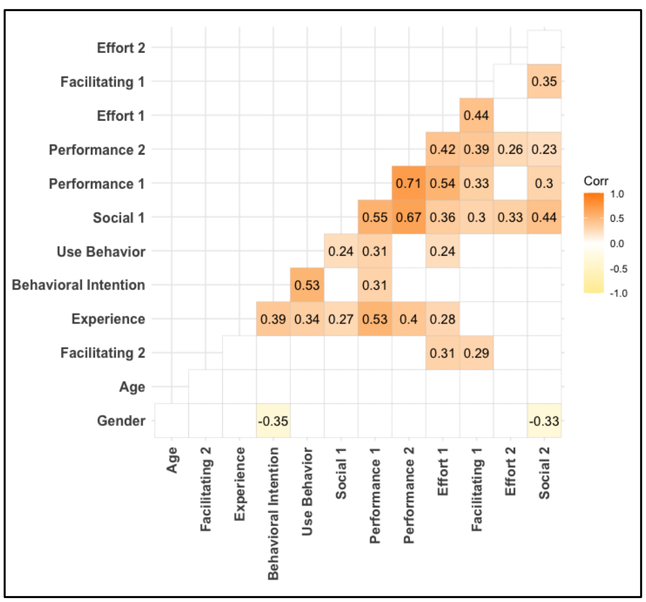

Figure 3: Correlation Matrix of Variables

Although the data is not highly correlative, there does exist some correlation values greater than 0.6. Pairwise variables with Pearson p values greater than .05 are removed from the correlation matrix. Thus, all correlation values shown are significant at the five percent level and denote a correlative relationship. For example, performance 2 has a correlation coefficient of 0.67 with social 1.

PLSR component loading factors are exhibited in Table 3 below, indicating characteristics most important in predicting use behavior. In traditional PLSR analysis, individual variable loading factors greater than .5 contribute to creating the latent component (Hair et al., 2006). Variables with a factor loading greater than or equal to approximately .5 in absolute value are highlighted to underscore their construction in creating the respective latent component. Variables that do not load into any components are left blank.

The driving factors of component 1, the variables with maximum predictive capabilities to describe use behavior, include Performance 1, Performance 2, and Social 1. These results are corroborated in Figure 2, as the correlation values of these characteristics exhibit the highest Pearson correlation coefficient. The constructs comprising component 1 indicate similar characteristics in forecasting student use of AI tools.

Components 2 and 3 comprise a single construct: Social 2 and Facilitating 1, respectively. This indicates that these constructs are important drivers of technology adoption but did not group with any other constructs. Student adoption of generative AI is uniquely driven by these constructs, and it is important for educators to incorporate them separately into the curriculum.

Table 3: Partial least squares regression (PLSR) loading factors

	Comp 1	**Comp 2**	**Comp 3**
Gender			
Age		-0.103	-0.346
Experience	0.298	-0.311	0.255
Behavioral Intention	0.193	0.236	0.32
Performance 1	0.521	-0.283	
Performance 2	0.529	-0.381	-0.295
Effort 1	0.352	-0.108	
Effort 2	0.183	0.221	-0.124
Social 1	0.495		-0.275
Social 2	0.323	0.818	-0.463
Facilitating 1	0.301	0.205	-0.646
Facilitating 2	0.201	0.354	

Table 4 below displays the total variation in the target variable, use behavior, explained by the formation of the three latent components found in PLSR analysis. The proportion of variance for each component indicates the variation accounted for in the response variable within the component. Component 1, comprising mostly of Performance 1, Performance 2, and Social 1, indicates that these three constructs can explain approximately 11 percent of the variation of use behavior. Component 2 defines the second most important component, as this latent variable can explain just under 11 percent of the variation in use behavior. Component 2 is constructed entirely by one variable, Social 2, indicating a strong association between this construct and use behavior. Component 3 is also a singleton, denoting that Facilitating 1 is a driver of use behavior. Component 3 accounts for approximately nine percent of the variation in use behavior.

The cumulative variance is a summation of all components. It indicates that all three components in this analysis account for 31 percent of the variation in student behavior in generative AI tools. Although the cumulative percentage of variation explained by the factors in this analysis is not extremely high, insights may still be gained about individual competencies driving technology adoption through the UTAUT framework.

Table 4: Partial least squares regression model variation explained

	Comp 1	Comp 2	Comp 3
SS loadings	1.316	1.295	1.114
Proportion Var	0.11	0.108	0.093
Cumulative Var	0.11	0.218	0.311

Discussion of Findings

The five UTAUT constructs loaded into three latent components as shown in Table 3. Model findings from the first component exhibit that students' intention to use AI tools is comprised of enabling productivity gains through the allowance of accomplishing tasks more quickly. Individuals who adopt AI technology also see productivity gains in the workforce (Noy & Zhang, 2023), further solidifying student motivations for adoption. In addition, another driver of adoption is students' mentors, or highly regarded individuals, who believe that AI use is important. Educators now have information that important individuals to students, perhaps professors themselves, influence students' decisions to adopt the technology. This information may act as reinforcement to embrace the role of AI by incorporating it into the curriculum.

Another construct influencing student use intention is the proportion of other students, or peers, who are using AI tools. Existing literature reports heterogeneity regarding social influence as a driving factor of generative AI adoption. According to Gupta (2024), empirical results indicate that social influence is an important factor in AI adoption. Conversely, data analysis provided by Matalka et al. (2024) finds that social influence does not play an important role in student usage of ChatGPT. The findings in this study are useful to educators as they support the debated idea that students are influenced by their peers. As students adopt AI systems swiftly, it suggests the rapid increase will continue and thus requires an immediate need for a common framework in academia.

The final construct driving adoption is that students believe AI tools are compatible with all aspects of their work. Educators should include information on the broad power of generative AI as systems, such as ChatGPT, which are trained on a large corpus of data utilizing 1.76 trillion parameters (Azaria et al., 2024). This large corpus allows for knowledge in a wide range of fields. Educators must teach students all the capabilities of generative AI tools to engage them. Students' familiarity with generative AI tools can broaden their learning and help them develop transferrable skills that will help them in their future careers. This could include using generative AI tools to explore topics not directly covered in their course. Instructing students on the universal tasks performed by generative AI may assist in driving adoption amongst the technology laggards.

Notably, none of the demographic characteristics load into latent components. Gender and age are not moderators influencing the constructs concerning student adoption of AI systems. In addition, previous experience using the technology and frequency of use did not drive specific use behavior, indicating that heavy users of AI are not adopting the tool for specific reasons, such as coding tasks. These findings support the driving factor of facilitating 1, that students adopt AI tools as they can perform a wide range of tasks.

Implications for future research

According to Sohn & Kwon (2020), the VAM model outperformed the UTAUT model, utilizing consumer purchases of artificial intelligence products. Given these findings, the researchers of this study wish to compare the findings in this investigation to the VAM model to determine if the results translate into student consumption of AI tools. The researchers ponder if the benefits of performance expectancy outweigh the costs of adopting AI systems. Future research could also use the same UTAUT framework and methodology examined in this study but with a larger and more robust sample size.

The sample size of this study is a potential limiting factor of indicative findings. There is also the potential for survey respondent bias in overstating or understating their adoption timeline or frequency of use. A self-selection bias exists as this survey was delivered through email to the entire student population at a small New England business school. Students who are more likely to assist researchers may introduce bias into the result as these students most likely exhibit similar academic characteristics.

Previous literature indicates both the benefits and costs of adopting AI tools in academia (Rahman & Watanobe, 2023). This research overwhelmingly examines the benefits of AI adoption while acknowledging that the costs associated with these tools are not well addressed in this research. The VAM model better examines the balance between the benefits and costs of technology adoption.

Conclusion

This study has investigated the UTAUT model to understand factors influencing the adoption of AI tools among college students. By analyzing survey results using a partial least squares method, we found that students are more likely to adopt AI tools if their mentors also use them. Students recognized the potential of AI tools across multiple courses and disciplines, and the value that proficiency with AI tools will bring to their future careers. These findings emphasize the need for educators to promote the proper and ethical use of AI in the curriculum. Finally, mediating factors such as gender, age, and prior experience did not significantly impact the adoption of AI technologies. Students choose to use AI tools to help them in a wide range of personal, academic, and professional purposes.

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