Journal of Business Administration Online
ARKANSAS TECH UNIVERSITY College of Business HTTPS://JBAO.ATU.EDU

Spring 2025, Vol. 19 No. 1

Factors that Influence University Students to Use (or Not Use) AI: A Behavioral Analysis

James P Downey, University of Central Arkansas

Alexander Chen, University of Central Arkansas

Tracy Suter, University of Central Arkansas

ABSTRACT

On February 1, 2023, Reuters' Krystal Hu reported that OpenAI's ChatGPT had reached 100 million users in January. A mere two months after its launch, this generative artificial intelligence (AI) technology was the fastest-growing consumer application in history. With its ability to generate written text, including essays, poetry, and even jokes, from a simple prompt, it presents opportunities and threats. We explore both in this study with a focus on the factors that contributed to the phenomenal growth as this technology has the potential to impact countless areas of public life, including business, government, and especially education. With a focus on college students and conducted in fall of 2023, early in the ChatGPT evolution, the study examines eight potential motivators gleaned from adoption and use models. It found that respondents were motivated to use AI by perceived usefulness, perceived affect, and perceived trust. It found that students were not motivated by several other common motivators--perceived ease of use, anxiety, perceived risk, social influence, or self-efficacy. The most surprising finding was that about 35-40% of students either did not use AI or used it rarely; these students were demotivated mostly by a lack of confidence in their ability to use AI (e.g., self-efficacy). There was a pronounced gender effect in the study, with females using AI much more and having significantly higher reported mean scores for all eight study measures (or lower scores for the posited negative relationships for anxiety and risk. The findings provide a nuanced picture of behavioral motivators to adopting and using AI -- as well as NOT adopting AI.

Keywords: Artificial intelligence (AI), generative AI, Technology Acceptance Model, computer self-efficacy, perceived trust and risk, anxiety.

INTRODUCTION

Artificial intelligence (AI), and in particular generative AI, has revolutionized many aspects of human-computer interaction. Its influence on business, government and education has been profound. It appears the innovation may approach the impact that the diffusion of the internet had in the 1990s. Higher education is now grappling with this collision and how to deal with it in a manner that preserves student learning yet permits its beneficial use. As with any new technology, understanding the factors behind its adoption and early use provides insight into the diffusion trajectory by the population of interest. There have been some early studies in the motivators of AI adoption and use, but much remains undiscovered. This study empirically examines why college students use, or do not use, generative AI technology. Using many of the seminal models that describe human behavior, and in particular technology behaviors, eight factors are examined that may motivate college students to make the decision to use or not use AI. These factors include perceived usefulness (PU) and ease of use (PEOU), perceived risk and trust (PR/PT), computer self-efficacy (CSE), positive affect (PAFF) and anxiety (ANX), and the influence of significant others (social influence--SI).

Using a survey instrument, the study was conducted in the fall of 2023, early in the generative AI revolution (ChatGPT was introduced in late 2022). The study found that respondents were motivated by three factors: perceived usefulness, positive affect, and perceived trust. There was also a pronounced gender effect evident in the study: females used AI significantly more often and for longer periods, and believed it had more usefulness, was easier to use, they had more perceived trust, self-efficacy, and were influenced more by significant others. They had less anxiety and perceived risk. The gender finding was surprising, given dissimilar findings in extant studies. Another surprising finding was that over half of the respondents either did not use AI or rarely used it. In examining the differences between these two groups, users were found to be significantly influenced by AI usefulness and liking the technology (positive affect). Non-users, on the other hand, had little confidence in their ability to use AI (low CSE), which was a significant barrier to use.

Generative AI clearly has some extraordinary benefits for business and other organizations, including universities. But as higher education is in the business of educating students, there is a conflict between student learning and allowing generative AI to produce output for students. Understanding the motivating factors that prompt students to use AI is a first step in understanding how to deal with this remarkable innovation. This study provides some clarity on this process of adopting and using generative AI.

LITERATURE REVIEW

With the advent of end user computing in the 1980s, there have been numerous studies that attempt to explain the adoption and use of a wide range of technologies by individuals. These studies have provided multiple models that examine motivators for an individual's decision to adopt and/or use a particular technology. One of the most influential is the Technology Acceptance Model (TAM; Davis, 1989), which holds that perceived usefulness (PU) and perceived ease of use (PEOU) are critical factors in technology adoption and use. Individuals are more likely to adopt and use a technology that helps their work or daily life, especially if it is easy to use. The original TAM model has undergone several extensions, which have added other motivating factors. Behavioral intention to adopt and use a technology was an early addition to the model (Davis, Bagozzi & Warshaw, 1989). A later addition was subjective norm, which found that adoption and use is influenced by the social expectations of significant others (Venkatesh & Morris, 2000); it was labeled TAM2 by Venkatesh and Davis (2000).

Perceived trust of the technology was also added as an extension to TAM (Gefen et al., 2003).

TAM itself has its roots in earlier models, including Rogers' theory of innovation diffusion (1962; 2003), which describes the process by which individuals adopt new ideas or innovations, from early adopters to laggards. A more proximal model was the Theory of Reasoned Action (TRA), which proposed that attitudes and subjective norm influences an individual's decision to adopt a behavior (Fishbein and Ajzen, 1975). Attitudes include positive affect and negative attitudes, such as anxiety; these attitudes either promote or demote an individual's willingness to adopt. A further refinement added perceived behavioral control to the model, labeled Theory of Planned Behavior (TPB; Ajzen, 1991). Perceived behavioral control is the confidence an individual has in their ability to control influences surrounding the behavior. Perceived behavior control itself has its roots in Bandura's Social Cognitive Theory (SCT; Bandura, 1986, 1997), which held that outcome expectations and self-efficacy influence the behaviors engaged in by an individual, their effort in pursuing the engagement, and their persistence in the face of difficulty. Self-efficacy is the degree to which an individual believes they can successfully carry out the behavior. Computer self-efficacy (CSE) applies Bandura's findings to the realm of information technology, with a plethora of extant studies which find a strong relationship between CSE and a variety of IT behaviors, including technology usage, skill development, and attitudes toward technology. The Unified Theory of Acceptance and Use of Technology (UTAUT2; Venkatesh et al., 2012) draws upon all these models (and more) in an attempt to unify these related models and their constructs which predict adoption and use of computer technologies. An extension added risk to the model, finding that one's perception of the risk involved influenced use of mobile shopping applications (Chopdar et al., 2018).

This alphabet of acronyms underlies the efforts of researchers and practitioners to unfold the motivators to adopting behaviors of interest. One of the enduring features of such models is that technologies change all the time and therefore these models are used repeatedly in different contexts. Another feature is that technologies differ in terms of the motivators for adoption and use. The motivating factors of TAM for example, while robust and well-validated, do not always significantly predict adoption and/or use. To take just one example, perceived usefulness has frequently been a significant predictor of using (or intending to use) technologies in an array of extant studies--but that hasn't always been the case. It did not significantly influence use of e-payment services among respondents in Japan (Chen et al., 2020), China (Nadler et al., 2019), or Indonesia (two studies: Immanuel & Dewi, 2020; Karomah et al., 2021). This suggests that the technology itself may have an impact on which factors impel users of a particular technology. In this study, we examine the burgeoning field of generative AI, examining the motivators of college students in their use of AI.

Generative AI and Higher Education

The rise of generative artificial intelligence in the past few years has reached historic levels. In 2023, ChatGPT, from OpenAI, set a record for the fastest-growing consumer application in history, reaching 100 million active users in just two months after launch, beating the previous records of Instagram (2.5 years) and TikTok (9 months) (Hu, 2023). This was after securing one million users in only five days (Duarte, 2024). With an ability to quickly generate high quality, contextually relevant content, its impact has changed the nature of human interaction with computers. Artificial intelligence has been around for decades. In the 1950s, Alan Turing proposed an imitation game, in which AI was evident if a human could not tell if a conversation came from another human or a machine (Popenici & Kerr, 2017). McCarthy probably coined the term "artificial intelligence" in 1956 (Russell & Norvig, 2010). Artificial intelligence itself is an umbrella term, spanning a multitude of methodologies which support or replace tasks originally carried out by humans. Early tools included the rule-based expert systems of the 1960s and 1970s. In the last twenty years or so, advancements in AI exploded, a phenomenon that is similar in impact to the advent of the Internet in the 1990s. Banh and Strobel (2023) divide the domain of AI into several subfields. Machine learning is one, and includes tools such as decision trees, k-nearest neighbors, and support vector machines. Deep learning is a more advanced subset of machine learning, represented by neural networks, which detect patterns in large datasets. Generative AI, a subset of both machine learning and deep learning, can generate fresh content based on large amounts of trained existing data. These large language models differ from previous models in that they are initiated not from data but from a prompt.

The impact of generative AI on higher education has been astonishing in just a short time. It has affected every facet of the educational process, including students, faculty, researchers and administration. It has been received by these groups in a multitude of ways. Edgell (2024) describes it poetically as a "monster [that] evokes fear and admiration as it simultaneously conjures utopian and dystopian futures" (p. 1). For students, it can aid the learning process, provide almost instant tutoring, and enhance employability. It can help teachers with lesson plans, developing new content, and even assist in grading. But there are challenges and fears. There is a clear concern with misusing AI, including cheating and other ethical ramifications. Some universities don't have the resources, such as computers and software, to use and/or teach AI effectively. Many educators fear that AI reduces a student's ability to learn conceptual building blocks in a discipline, including expressing thoughts by writing coherently. To cite just one example of conflicting beliefs toward AI, some suggest that the use of AI stifles student creativity (Edgell, 2024). Others find that AI significantly enhances creativity (Habib et al., 2024). Generative AI still has difficulties with some of the more complex tasks of higher learning, including the ability to distinguish irony, sarcasm or humor (Popenici & Kerr, 2017).

While the debate over positive or negative aspects of generative AI continues, this study is primarily interested in examining how much students use AI and the motivators behind such use. What impels college students to use (or not use) generative AI? As with many studies involving adoption and use of technology, this study examines the motivators validated in the many models mentioned, including TAM/TAM2, TRA/TPB, CSE, and UTAUT2. As a starting point, this study expects that the motivating variables in these models will also influence use of AI. Generative AI is a technology, and adoption and use of this technology is likely to be driven by these same factors.

Hypothesis Formulation

To examine the motivators for the use of AI among college students, the models of technology adoption and use already mentioned are used. These include TAM/TAM2, TRA/TPB, CSE, and UTAUT2. Given the newness of this phenomenon among university students, the intent was to include as many potential predictors as possible, to provide a foundation for any future, more focused examination. Besides demographic variables, this study included the following eight potential influences on generative AI adoption and use: perceived usefulness, perceived ease of use, social influence, computer self-efficacy, positive affect, negative affect (anxiety), perceived risk and perceived trust.

Perceived Usefulness**.** Perceived usefulness (PU) is the degree to which an individual believes using a particular technology will enhance their personal or professional performance (Davis, 1989). This construct is one of the foundational motivators in studies of technology adoption the last thirty years and it has consistently been a significant predictor in a variety of different contexts and technologies. A technology which is useful and enhances performance is one that appeals to users. It is similar to outcome expectations in social cognitive theory (Bandura, 1986; 1997). While PU has a long history of being a significant predictor of technology use, it has already appeared as a significant motivator in AI studies. In one study, it significantly predicted the intention to use AI financial robo-advisors (Flavian et al., 2022). It was significantly related to AI adoption among accounting students in Indonesia (Sudaryanto et al., 2023). Given its history, including AI studies, the following hypothesis is offered:

H_1: Perceived usefulness (PU) is positively related to AI usage.

Perceived Ease of Use**.** Perceived ease of use (PEOU), as articulated by Davis (1989), reflects the perceptions of potential users regarding the challenges inherent in using an application. Technologies that are complex to use are less likely to be adopted than a user-friendly one. Like PU, it is one of the original TAM constructs and has been found to significantly influence technology use in a multitude of settings. It supports Rogers' theory of innovation diffusion (2003), where adoption speed is influenced by complexity and compatibility. It has been significant in predicting technology adoption and use in many different technologies, cultures, and settings. It has been a significant predictor in early studies of adopting AI technologies as well (Flavian et al., 2022; Sudaryanto et al., 2023). This leads to the following hypothesis:

H_2: Perceived ease of use (PEOU) is positively related to AI usage.

Social Influence**.** Social influence and subjective norm are often used interchangeably and refer to the influence of significant others in the decision to adopt a behavior. A foundational motivator in TRA and later TAM2, the persuasive powers of critical others can influence an individual's decision to adopt a particular behavior (Ajzen & Fishbein, 1980). Significant others may include family members, employers (bosses and co-workers), teachers or friends. It has been a significant influence in a variety of technology adoption studies for decades, including mobile phone service (Chen & Chang, 2013) and the technology WeChat for health services (Wu & Kuang, 2021). Social influence has also had a positive influence on intention to use generative AI technology (Bouteraa et al., 2024; Polyportis & Pahos, 2024). The following hypothesis is thereby offered:

H_3: Social influence (SI) is positively related to AI usage.

Computer Self-efficacy. According to Social Cognitive Theory (SCT), an individual tends to choose behaviors in which there are positive outcome expectations and in which they have some level of confidence in successfully carrying out the behavior (Bandura, 1986, 1997). The level of confidence, or self-efficacy, is not merely a passive indicator but motivates one to marshal the resources necessary to carry out the behavior, in terms of effort expenditure and persistence in the face of obstacles. This has been applied to technology behaviors; computer self-efficacy (CSE) has long been a significant positive influence on computing behaviors. This includes technology applications such as spreadsheets and word processing, where CSE strongly predicted competence in those applications (Compeau & Higgins, 1995; Downey & Rainer, 2007). It has been found to significantly influence use of generative AI as well, using two different self-efficacy measures. Educational self-efficacy (confidence in one's higher education prowess) and computer self-efficacy both significantly influenced use of AI (Bouteraa, et al., 2024). This leads to the following hypothesis:

H_4: Computer self-efficacy is positively related to AI usage.

Attitudes. Positive Affect and Anxiety. An attitude may be defined as 'a learned predisposition to respond in a consistently favorable or unfavorable manner' towards a domain (Fishbein and Ajzen 1975, p. 6). They are dynamic, domain-specific individual differences that affect the conduct of the individual's activities within the domain (Thatcher and Perrewe, 2002). Attitudes toward technology influence the behaviors associated with learning and using the technology. Individuals who have more positive feelings and less anxiety are more motivated to use a technology. Attitudes also affect how an individual perceives future outcomes, such as career growth, job choice, and performance, which enhance skill acquisition through their usefulness. This study includes two attitudes, positive affect and anxiety.

Positive affect. Positive affect is the feeling of like or dislike towards a domain, in this case technology and specifically AI. An individual who likes technology is more apt to use it than one that does not like it. Positive affect has been shown to influence computer usage (Al-Jabri & Al-Khaldi, 1997). It has also demonstrated influence on the use of generative AI (Bouteraa et al., 2024; Polyportis & Pahos, 2024). Yet not all studies share the same result. Positive affect did not influence university faculty to use AI tools for teaching (Wang et al., 2021). These mixed results indicate additional study is important. Despite these contradictory findings, the following hypothesis is presented:

H_5: Positive affect (PAFF) is positively related to AI usage.

Anxiety. Computing anxiety is a fear of computers or of computer use (Loyd and Gressard, 1984). It is a domain-specific fear and is distinguishable from trait anxiety, which is a general feeling of anxiety (Thatcher and Perrewe, 2002). Computer anxiety is influenced by a variety of emotional and environmental factors (Marakas et al. 1998). Like any attitude, anxiety influences choice of behavior, motivation to learn, effort, and persistence. Those with higher anxiety tend to not use a technology (or use it less often), while those with lower anxiety tend to use it more. Anxiety has been a significant negative influence in many technology endeavors, including competence (Downey & Smith, 2011). It has mixed results in early studies of generative AI, however. One study found it significantly (negatively) influenced college students use of ChatGPT (Bouteraa et al., 2024). In another study of university faculty, it was not significant in using AI tools for teaching (Wang et al. 2021). Such conflicting findings suggest further studies are important. The following hypothesis is presented:

H_6: Anxiety (ANX) is negatively related to AI usage.

Perceived Risk. Perceived risk refers to the degree of personal, financial, or transactional risk involved in a transaction. It has an extensive research stream in psychological and human behavior research. Higher risk has long been negatively associated with adoption and use behavior. The riskier an individual perceives the technology interaction, the less likely adoption and use will occur. Using UTAUT2, Chopdar and associates (2018) added privacy and security risk to the model and found that both significantly influenced use of mobile shopping applications in India and the US. Higher risk was associated with lower frequency of use for e-payment technology (Chen et al., 2023). In a recent study of intention to use AI for robo-advisors, insecurity significantly influenced its use (Flavian et al., 2022). Therefore, the following hypothesis is proposed:

H_7: Perceived risk (PR) is negatively related to AI usage.

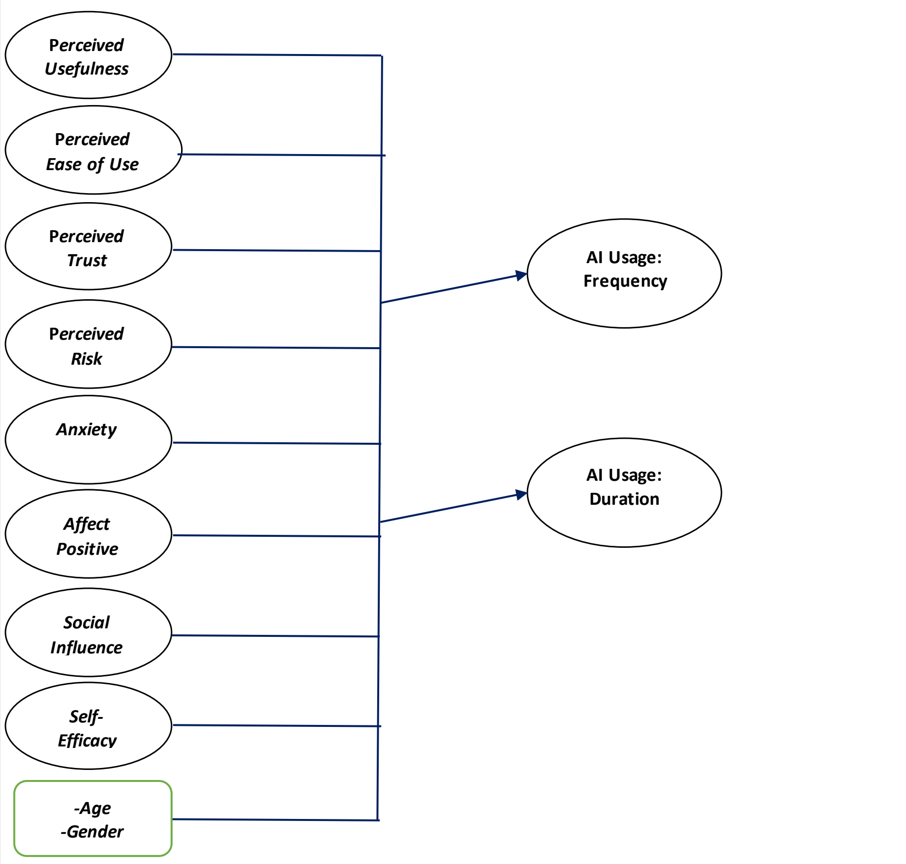
Perceived Trust. Perceived trust is an individual's belief that the transaction (whatever it may be) will be in accordance with perceived security expectations (Kallanmarthodi and Vaithiyanathan, 2012). Gefen et al. (2003) added trust as an extension to TAM and defined it as the willingness to depend on or to be vulnerable to another party based on their abilities, benevolence, and integrity. Using the domain of online exchanges as an example, past studies concluded that trust was an important predictor of user's willingness to use online exchanges (Barkhordari et al., 2017; Gefen, 2000). In the realm of generative AI, it significantly predicted positive attitudes toward ChatGPT (Polyportis & Pahos, 2024). Interestingly, in another longitudinal study spaced eight months apart, trust in AI significantly decreased (Polyportis, 2024). Despite these mixed results, the following hypothesis is presented:

H_8: Perceived trust (PT) is positively related to AI usage.

Demographic influences. In this study, two demographic variables were included: gender and age. While not included in any hypothesis, both age and gender have been known to impact use of technology across a multitude of studies. They are included in this exploratory study.

The research model is displayed in Figure 1:

Figure 1. Research Model



Conflicting Findings

While many studies support the factors presented as significant motivators of technology adoption and use, it must be noted that there have been mixed findings. Some have already been mentioned. It is not universal that the various motivating factors used in this study predict or influence technology adoption and use. It appears that the context may make a difference. Indeed, this is one of the primary reasons for this study, to examine college students' adoption and usage behaviors for generative AI. Is ChatGPT adoption, for example, influenced by how easy it is to use or the person's attitudes? The literature has many examples of studies where one or more of the factors used in this study did not significantly influence usage of a particular technology.

Using just one relatively recent technology as an example, the use of e-payment systems, the literature is quite mixed in its findings. Perceived usefulness was not significant in influencing usage in Japan (Chen et al., 2020), China (Nadler et al., 2019) or Indonesia (Immanuel & Dewi, 2020; Karomah et al., 2021). Perceived ease of use was not significant in studies in the U.S. (Chopdar et al., 2018), China (Nadler et al., 2019), Japan (Chen et al., 2020) or Iran (Barkhordari et al., 2017). Perceived risk was not significant in the U.S., but was in China (Chopdar et al., 2018). Neither perceived risk nor trust were significant in a study in Iran (Barkhordari et al., 2017). Social influence was not significant in either the U.S. or India (Chopdar et al., 2018). It seems clear that the motivators associated with a particular technology depend in part on the technology.

This study examines the influence of several potential motivating factors on the use of generative AI tools among college students. It draws on multiple extant models that have been used in helping to define the motivating factors of an individual's interaction with technology. These models include TAM/TAM2, TRA/TPB, CSE, and UTAUT2. The inclusion of multiple motivators should enhance the findings for the relatively new technology of generative AI. It will help educators, businesses and other organizations understand the factors that propel individuals to use this technology.

RESEARCH METHODOLOGY

Participants

The participants for this study were students from a medium-sized state university in the mid-south of the U.S., who participated in a voluntary survey. The survey was conducted in the fall of 2023, which places it early in the rise of ChatGPT, one of the most common generative AI platforms. This is an important timing distinction, as it permits the study to examine the motivators among young adults for a relatively new technology. There were no incentives involved in the survey, but it was publicized by the university.

The survey was sent out via email to the student population, about 9,000. It is not known how many actually opened up the email. There were 523 returned surveys, but of these, 243 were discarded as incomplete. Most of these discarded started it but did not finish (leaving 50 or more unanswered questions). This left a total of 280 usable responses. About 53% were male and 30% female (the rest classified as other). On average, respondents were 25 years old. Approximately 75% were undergraduate students, 25% graduate students. About 48% were classified as either juniors or seniors. Students were evenly divided, about 20% each, among the university's academic colleges: Arts & Humanities, Science/Engineering, Business, Education, and Health Sciences. Demographic information is provided in Table 1.

Study Measures

All of the measures in this study have been previously reported and validated. However, all were modified so that the technology in question was "AI tools". Many of the constructs came from Teoh et al. (2013), including perceived usefulness (PU), perceived ease of use (PEOU), perceived risk (PR), perceived trust (PT) and social influence (SI). These measures used a 7-point Likert scale ranging from 1 (Completely disagree) to 7 (Completely agree). The self-efficacy scale (CSE) came from the original general computer self-efficacy scale of Compeau & Higgins (1995). This measure used a seven-point confidence scale ranging from 1 (Not at all confident) to 7 (Totally confident). The survey items are provided in Appendix A.

Table 1. Demographic information

Variable		Frequency	Percentage
Gender	Male	163	58.2%
	Female	91	32.5%
	Other	26	9.3%
	Total	280	100%
Age	17-20	108	38.8%
	21-30	116	41.7%
	31-40	24	8.6%
	41-50	24	8.6%
	51+	6	2.2%
	Total	278	100%
Education	FR	40	14.3%
	SO	36	12.9%
	JR	61	21.8%
	SR	71	25.4%
	Grad	69	24.6%
	Other	3	1.1%
	Total	280	100%

AI usage can be defined simply as one's personal use of a generative AI tool to glean information or content; it may be used for any purpose, including school or work or for personal reasons. It was measured two ways, through frequency and duration. Frequency was assessed through a seven-choice ordinal instrument that asked how often a respondent used "ChatGPT or other similar tools". Responses ranged from 1 (Never), 2 (Less than once a month) to 7 (Several times a day). Duration was measured as the length of time a respondent used AI in an average week. It ranged from 1 (No time at all), 2 (Less than an hour) to 8 (10+ hours). The two different measures of AI usage enhanced the model by providing two dependent variables.

RESULTS

This study examined the relationships among college students between AI usage and several potential motivators, gleaned from established models of technology adoption and use. These factors included perceived usefulness (PU), perceived ease of use (PEOU), perceived trust (PT), perceived risk (PR), anxiety (ANX), positive affect (PAFF), social influence (SI) and computer self-efficacy (CSE). These relationships were examined through the tools of correlations and multiple regressions. The first step in the data analysis was confirmatory factor analysis to confirm each independent variable scale was unidimensional. Most were, including PU, PEOU, PT, and CSE. The perceived risk scale included five items and when factor analyzed, two items had low loadings and were eliminated. Low loadings also eliminated two items from the anxiety scale and two from the social influence scale. Scale reliability using Cronbach's alpha of the resulting constructs were high or relatively high, with only perceived risk lower than .85 (at .814).

Respondents reported that AI tools were fairly easy to use (4.86 mean on a 7-point scale) and that they were useful (4.37 mean). They reported relatively high levels of perceived risk, with a mean of 4.64 (of 7); the higher the number, the more risk they felt in using AI. Perceived trust, anxiety and affect had means right near the center of the scale, indicating moderate levels of those motivators. Respondents reported fairly high AI computer self-efficacy (4.62), indicating they felt confident using AI. Interestingly, social influence scored the lowest, with a 2.91 mean, suggesting that respondents were not all that motivated by the influence of family, friends, employers and peers. Descriptive statistics and alphas are presented in Table 2.

Table 2. Descriptive Statistics and Alphas of IVs

Construct	# items	Mean	SD	Alpha
PU	5	4.37	2.04	.973
EU	5	4.86	1.61	.959
PT	4	3.18	1.49	.914
PR	3	4.64	1.63	.814
ANX	4	3.52	1.57	.881
PAFF	4	3.33	1.45	.856
SI	2	2.91	1.59	.895
CSE	9	4.62	2.25	.974
All scales had a range of 1-7.				

AI usage information was provided using two different measures, frequency and duration. Frequency measured how often a respondent used AI tools and ranged from 1 (Never) to 7 (Several times a day). Duration measured the average number of hours per week a respondent used AI. The responses ranged from 1 (No time at all) to 8 (10+ hours). Perhaps the most interesting finding was that a large number of students reportedly did not use AI much at all. Over 38% reported they never used AI tools, which was matched by about 46% who reported their duration of use was no time at all. About 55% reported using it once a month or less. 78% reported using it less than hour. It is apparent that AI tools in this particular time frame, fall of 2023, this group of college students were mostly non-users. While this was somewhat surprising, the motivation for using (or not using) will still be an important finding from this study. Why haven't these students started using AI, at least yet? And for those that do use AI, what are their motivators? Table 3 presents usage information.

Table 3. Usage Statistics

Usage Frequency				**Usage Duration (weekly)**			
#	**Item**	**Freq**	**%**	**#**	**Item**	**Freq**	**%**
1	Never	107	38.4%	1	No time at all	128	45.9%
2	About once a month	48	17.2%	2	< 1 hour	92	33.0%
3	Few times a month	0	0%	3	1-2 hours	35	12.5%
4	About once a week	58	20.8%	4	3-4 hours	18	6.5%
5	Few times a week	47	16.8%	5	5-6 hours	4	1.4%
6	About once a day	8	2.9%	6	7-8 hours	1	.4%
7	Several times a day	11	3.9%	7	9-10 hours	1	.4%
				8	10+ hours	0	0%

The correlation matrix includes both dependent variables, all eight motivators, plus gender and age. Correlations between the variables were mostly significant and all were in the appropriate direction. The correlation between the two dependent variables, AI frequency of use and duration was .831 and had the highest correlation between any two variables. This indicates a measure of content validity as these two measures of AI usage were expected to be similar. The only non-significant correlations involved age, which was not significantly related to most of the other constructs, including the dependent variables. Age was only significantly correlated with social influence, perceived risk and positive affect. Excluding the two demographic variables of gender and age, all of the correlations were in the expected direction. Perceived risk and anxiety were negatively related to all other variables (except each other); all other variables were positively related. The correlation matrix is provided in Appendix B. This appendix provides all correlations; for hypothesis testing (below), correlations are used which focus on the dependent variables.

Hypotheses Testing

To test which motivators significantly influenced a student's decision to use or not use AI, correlations and multiple regression analyses were used. Correlations were used to test whether each motivator variable independently had a significant relationship with each dependent variable (a pair-wise comparison). This provides the same significance as simple regression. Next, multiple regression was used to test the strength of all independent variables simultaneously, in order to determine which variables were significantly stronger. Two separate models were created, given that there were two measures of AI usage (frequency and duration). Also included in each model were the demographic variables of age and gender.

Table 4 presents the findings. Almost all independent variables were significantly correlated with the two measures of usage. The only variable not significant was age. Age seems to have little to no impact on AI usage among these respondents. Led by perceived usefulness and positive affect, all the other variables were significantly associated with the two usage measures.

Table 4. Correlations and Multiple Regression Results

Usage Frequency (R^2 = .574)					**Usage Duration (R^2 = .446)**				
	Corr.	**β**	**t**	**p**		**Corr.**	**β**	**t**	**p**
PU	.63***	**.40**	**5.17**	**.001***	**PU**	.54***	**.33**	**3.75**	**.001***
PAFF	.67***	**.28**	**3.29**	**.001***	**PAFF**	.60***	**.32**	**3.33**	**.001***
PT	.50***	**.15**	**2.22**	**.027***	**PT**	.44***	**.17**	**2.18**	**.030***
PR	-.41***	-.09	-1.53	.129	SI	.42***	.10	1.68	.095
Age	.04	-.07	-1.49	.138	Gender	-.15**	-.054	-.98	.328
CSE	.40***	.08	1.34	.183	ANX	-.38***	-.077	-.95	.343
ANX	-.50***	-.08	-1.16	.249	CSE	.32***	.029	.42	.328
Gender	-.25***	-.05	-1.02	.308	PR	-.31***	-.026	-.37	.713
PEOU	.55***	.07	.92	.361	PEOU	.45***	-.028	.35	.676
SI	.39***	.03	.48	.632	Age	.09	-.02	-.29	.774

β: standardized betas. ** p < .01; * p < .05. PU: perceived usefulness. PEOU: perceived ease of use. PT: perceived trust. PR: perceived risk. ANX: anxiety. CSE: computer self-efficacy. In bold: significant multiple regression results.

Two multiple regression analyses were carried out and both demonstrated significant results. These are also presented in Table 4. The amount of variance explained by the models was .574 for frequency of use and .446 for usage duration. For both models, there were only three significant predictors: perceived usefulness, affect and perceived trust. All of the other independent variables were not significant in the regression analysis, including perceived risk, computer self-efficacy, anxiety, ease of use, social influence and the two demographic variables of age and gender.

There were eight hypotheses, one for each of the independent variables of PU, PEOU, SI, CSE, PAFF, ANX, PR and PT. Each motivator had a significant relationship with both dependent variables, AI usage frequency and duration. Using correlation data, this indicates that all hypotheses were supported. Because the motivators are themselves correlated, multiple regression provides a more nuanced analysis of the significant influences of AI usage behaviors. While not hypothesized, age and gender are also included. The results, using multiple regression, are presented in Table 5.

Table 5. Hypothesis Testing Results

Hypothesis		Frequency	Duration
1	PU	Supported	Supported
2	PEOU	Not supported	Not supported
3	SI	Not supported	Not supported
4	CSE	Not supported	Not supported
5	PAFF	Supported	Supported
6	ANX	Not supported	Not supported
7	PR	Not supported	Not supported
8	PT	Supported	Supported
	Age	Not significant	Not significant
	Gender	Not significant	Not significant

The same three motivators significantly predicted usage behaviors for both models. This included perceived usefulness, positive affect and perceived trust. Therefore, hypotheses 1, 5 and 8 were supported. All of the other potential motivators, as well as age and gender, were not significant in the two regression models.

Users vs. Non-users

While such findings are useful and portray behaviors among respondents early in the generative AI adoption life cycle, one of the more surprising findings was that many of the respondents did not use AI at all. This prompted the perhaps obvious question of "why"? In order to drill down into this issue, the respondents were divided into two groups, non-users and users. Non-users were those who reported never using AI or using it "About once a month". This corresponded exactly to those who reported using AI for "No time at all" or "Less than one hour" per week. Users were those who reported a frequency of "A few times a month" *or more* and a duration of "1-2 hours" a week *or more*. There were 154 non-users and 126 users (280 total).

After dividing the respondents into these two groups, t-tests were run to examine the differences between all the motivators between the two groups. Table 6 presents the results. Except for age, all other indicators showed significant differences between the two groups, some quite extreme. Users had significantly higher means for perceived usefulness, positive affect, ease of use, computer self-efficacy, perceived trust and social influence, as indicated by the negative sign. Non-users had higher means for anxiety and perceived risk--indicating that this group was more anxious about using AI and thought it was riskier. Gender was also significantly different and is discussed below.

Table 6. T-tests for Differences Between Non-users and Users

	Age	Gender	PU	PEOU	SI	CSE	PAFF	ANX	PR	PT
mean (N)	1.93	1.99	3.20	4.14	2.39	3.75	2.53	4.19	5.26	2.56
mean (U)	1.94	1.60	5.61	5.74	3.52	5.47	4.28	2.67	3.92	3.92
sd (N)	1.06	.46	1.67	1.61	1.39	1.83	1.19	1.48	1.53	1.31
sd (U)	.95	.92	1.17	1.01	1.57	1.2	1.05	1.20	1.37	1.29
t-value	**-.01**	**3.86****	**-16.42****	**-11.75****	**-7.65****	**-11.12****	**-13.70****	**10.86****	**9.25****	**-9.82****
N: non-user. U: user. ** p < .001										

In addition to t-tests, multiple regressions were run for both users and non-users for both dependent variables (frequency and duration). For non-users, frequency of use was only significantly related to computer self-efficacy, and it was a negative relationship (as expected). The primary barrier for use was a lack of confidence in their ability to use AI. The regression using duration as the dependent variable was not significant (F = 1.55, p = .13). The standard deviation of the dependent variable was too small (.38), given that the values for non-users were restricted to either 0 (No time at all) or 1 (Less than one hour per week). Users on the other hand were motivated by perceived usefulness and to a lesser extent, positive affect, using frequency of use as the dependent variable. For duration, positive affect significantly influenced users; there was also an age effect. Users liked AI and thought it useful. The older users used AI for longer periods. Table 7 provides multiple regression analyses for both non-users and users. Only p-values less than .20 are shown.

Table 7. Users and Non-users' Motivators

	Usage Frequency				**Usage Duration**			
		β	**t**	**p**		**β**	**t**	**p**
Non-users	**CSE**	**.26**	**2.78**	**.01****	Regression not significant (F = 1.55; p = .13)			
	PU	.21	1.67	.10				
Users	**PU**	**.30**	**2.60**	**.01****	**PAFF**	**.31**	**2.39**	**.02***
	PAFF	*.27*	*1.80*	*.07+*	*Age*	*.16*	*1.69*	*.09+*
	PEOU	.18	1.36	.18	PT	-.16	-1.42	.16
					PU	.16	1.32	.19
β: standardized betas. ** p < .01; * p < .05; + p < .10. Only independent variables below p < .20 are shown. In italics: p values between .05 and .10.								

Gender Effect

There was a significant gender difference between users and non-users, as reported in Table 6. Respondents indicated their gender as female (91), male (163), would rather not specify (11) or other (15). To examine this effect, respondents were divided into three groups, females, males and an “other” group that encompassed the remaining ones (total of 26). Table 8 presents group means and t-tests on the differences between females and males. Examining the means for the “other” group, the means in every case were below that of either females or males. This was true except for anxiety and perceived risk, where their mean was higher (indicating more anxiety and perceived risk). While not shown in the table, this group was significantly different than its closest neighbor, males. What is shown in the table are the t-test results for the difference in means between females and males. Except for age, in all other cases females used AI more and for longer, and were more motivated by usefulness, ease of use, social influence, computer self-efficacy and perceived trust. They had less anxiety and perceived risk about using AI.

Table 8. T-Tests for Differences in Gender

	Age	Freq	Dur	PU	PEOU	SI	CSE	PAFF	ANX	PR	PT
mean (O)	1.76	1.88	1.48	2.96	4.38	2.50	3.42	2.35	4.47	5.43	2.40
mean (M)	1.99	2.56	1.74	4.15	4.66	2.74	4.42	3.16	3.76	4.79	3.08
mean (F)	1.88	3.63	2.22	5.06	5.39	3.32	5.08	3.90	2.79	4.24	3.58
sd (M)	1.03	1.75	.94	1.83	1.63	1.54	1.70	1.40	1.55	1.54	1.47
sd (F)	.98	1.97	1.24	1.81	1.40	1.57	1.69	1.36	1.36	1.62	1.36
t-value	**.88**	**-5.91****	**-3.48****	**-5.03****	**-4.56****	**-3.51****	**-3.71****	**-4.79****	**6.21****	**3.36****	**-3.18****

T-tests apply only to female/male (NOT others). O: other/unspecified. M: male. F: female. ** p < .01
Males: 163 (53.3%). Females: 91 (29.7%). Other: 26 (8.5%).

Discussion

This study examined the motivators of AI usage among college students employing several influential models of human behavior, including the Technology Acceptance Model and its extensions (TAM/TAM2), the Theory of Reasoned Action and Theory of Planned Behavior (TRA/TPB), Social Cognitive Theory and Computer Self-efficacy (SCT/CSE), and the Unified Theory of Acceptance and Use of Technology (UTAUT2). From these models, eight motivators were proposed to influence AI usage behaviors among students, along with age and gender. Using correlation analyses, results indicate that all variables except age were significantly correlated with both AI usage frequency and duration of use (weekly average). Using multiple regression analyses, for both frequency and duration, there were three significant motivators: perceived usefulness, positive affect and perceived trust. All of the other indicators were not significant. These respondents used (or did not use) AI based on its usefulness, how much they liked it, and trusted it.

Perhaps the most critical finding was the lack of AI use among many of the respondents. At a time when AI use was burgeoning (fall of 2023), many of these college students did not use or rarely used AI. This finding prompted a diversion to the examination of the differences between non-users and users, and what motivators exist for each group. Non-users were defined as those who reported a frequency of 1 (Never use) or 1 (using it about once a month). Users were defined as those using AI a few times a month or more. Using duration as the measure of use, non-users reported using AI "no time at all" or less than 1 hour per week. As reported in Table 6, there were significant differences in means between users and non-users for all motivators, as well as a gender difference. The difference between the two groups was most significant regarding perceived usefulness, with a t-value of 16.42. But other motivators also had large t-scores, indicating users across the board liked AI more, had more positive affect, trust and self-efficacy, and less anxiety and perceived risk. These findings reinforce the notion that non-users are really just that – non-users.

The question, though, is why do non-users not use? What are their barriers to using AI? The multiple regressions performed on the two groups individually provide some insight. Users were motivated to use AI by the reasons already discovered – AI was useful and they liked using it. PU and PAFF were the most important motivators for using AI more frequently and for longer periods. Non-users, on the other hand, were demotivated by self-efficacy. Non-users had little confidence in their ability to use AI and this negatively affected their use of it. If administrators or faculty want college students who do not routinely use AI to use it, then enhancing their self-efficacy is a promising way to start. Bandura (1997) recognized four avenues for increasing one's self-efficacy for a task: enactive mastery (practice the task), vicarious experience (watch others perform the task), verbal persuasion (and other social influences) and affective states (improve positive affect and reduce anxiety). Allowing students the freedom to use AI can enhance CSE by promoting its use – which is the most effective way to increase CSE. Endorsing the usefulness of AI (vicarious experience and verbal persuasion) can help non-users improve their attitudes towards it, also enhancing CSE. Interestingly, non-users were not influenced by risk. This was expected to be a significant factor; students might be unwilling to use AI because it could be considered cheating or it could produce incorrect answers. This was not the case for these respondents; neither users nor non-users were unduly influenced by risk.

The results showed some other interesting findings. In particular, both demographic variables provided some insight into AI usage.

Gender. One's gender had a significant influence on the use of AI. Except for age, in every case females used AI oftener and longer than their male counterparts. They thought it more useful, easier to use, had more self-efficacy in using it, more trust, and more positive affect towards it. They had less anxiety and perceived risk using it.

This is borne out by the summary information in Table 9; most females used AI (63%) and most men did not (61%).

Table 9. Gender vs. Users/Non-users

	Females	Males
Users	57 (63%)	64 (39%)
Non-users	34 (37%)	99 (61%)
Only includes female/male data		

This finding was unexpected, as most previous AI studies including gender revealed no significant relationship (Flavian et al., 2022; Polyportis, 2024; Polyportis & Pahos, 2024). Another study concluded that gender had a small, moderating effect on the relationship between habit and intention to use AI, but little moderating effect on the other relationships between intention to use and PU, PEOU, SI, facilitating conditions, hedonistic motivation and customer value (Maican et al., 2023). In the Maican et al. study, it was males who displayed a higher intention to use AI (generating images for business purposes). Yet in the current study it was females who displayed a greater willingness to use AI and were motivated by the factors included in the study. There are potential reasons for this. In his theory of innovation diffusion, Rogers (2003) lists five stages as individuals move along the continuum from early adopters to laggards. These stages include knowledge (awareness of the innovation), persuasion (formation of positive or negative attitudes toward the innovation), decision (engaging in activities that either adopt or reject the innovation), implementation and confirmation. Females in this study have formed positive attitudes toward AI use and are in the implementation/confirmation stages. Males are lagging behind; as a group, they seem to be situated in one of the first two stages. From our data, it is unknown how much knowledge of AI the males possessed; but it does show that their attitudes towards AI were significantly different than their female counterparts. Males in this study clearly had less positive affect towards AI.

Age. For the most part, using or not using AI was not influenced by age. Previous studies of age and AI use were mixed. One study found that younger respondents intended to use AI (robo-advisors) more than older ones (Flavian et al., 2022). Others found age not significant (Polyportis, 2024; Polyportis & Pahos, 2024). Age was not significantly correlated with either of the two dependent variables or most of the motivating factors. It was significantly related to three motivators: older respondents liked AI more (correlation: .17) and were more influenced by significant others (.20) and negatively influenced by risk (-.19). Age was insignificant in all of the multiple regression analyses, though it approached significance for duration of use for the user group ($t = 1.69$; $p = .09$). Thus, there was a small but significant age affect for three of the motivating factors, but for the most part, age was not an influence for these respondents. The decision to use or not use AI was not really impacted by one's age.

LIMITATIONS, FUTURE RESEARCH AND CONCLUSION

This study examined the use of AI among college students in the early stages of AI diffusion, using two measures of AI usage and multiple motivating factors. It provides some clarity on the motivating (or demotivating) factors among college students as they make decisions on using AI in their academic, work or personal lives. This study found that many respondents either did not use or rarely used AI. Those that did use AI were motivated mostly by positive affect (they liked using it) and by its usefulness. Those that did not use AI much had little confidence in their ability to do so (CSE), which was a barrier to use. There was a pronounced gender effect in this study; females used AI more and for longer periods of time and had significantly higher levels of perceived usefulness, ease of use, trust, self-efficacy, social influence and positive affect. They had significantly less anxiety and perceived risk in using AI.

There were multiple limitations in this study. The respondents were from a single mid-south U.S. university and generalizing to other U.S. (or international) college-age students must be done cautiously. The survey was conducted at a single point in time – relatively early in the AI "revolution" and therefore is indicative only for that period of time. Its purpose, however, was to examine factors early in the diffusion period and therefore it may well be indicative of other individuals in the same period of time. The study examined eight motivating factors, and while these are recognized as critical ones, there are other factors that may also be influential in the adoption and use of AI technology. Future studies could include some of these, such as technology experience or cultural influences. This study also did not account for any work-related use of AI, which could have impacted the findings.

Future Research Streams. This study was carried out early in the advent of generative AI. Its purpose was to examine the motivators of students to use or not use this new technology. As diffusion of this technology occurs in the near future, as it is extremely likely to do, use of AI will transition from early adopters to mainstream and the motivators which propel and impel students may very well change. Future research efforts can document these potential changes, adding to the literature of how and why individuals continue to use a particular technology. Post adoption IT behaviors may differ substantially from early adoption and may differ depending on the technology (Ortiz de Guinea & Markus, 2009). An understanding of how and why these changes occur will help future educators and indeed business managers of any kind to formulate ways to most effectively and efficiently use AI in support of organizational goals. Applying similar future studies to other contexts, such as business and government, can help distinguish similarities and differences in the targeted population (students versus mid-level managers, for example). The gender differences noted in this study is also noteworthy; future studies might elicit whether this can be generalized to other groups (not students) and whether this also applies to post-adoption behavior of AI use. If it is a worthwhile goal to use generative AI ethically to enhance one's individual performance in support of organizational priorities in education, business, or government, then an understanding of the motivating factors that enhance usage and how they may change over time is critical.

This study illuminates some of the motivating factors of students in their decision to use generative AI. It makes no judgement on AI itself – the pros and cons of using such a technology in the college classroom – except to admit that it seems here to stay and is useful. At a minimum it seems that faculty should be aware of AI and understand that students are and will continue to use it in ever-greater numbers. It seems incumbent on faculty and administrators in universities to be prepared to cover if not use AI in the classroom with students. There seems little doubt that this innovation is here to stay and is making a profound impact on higher education. Using AI wisely seems the appropriate choice.

REFERENCES

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, 50(2), 179–211. DOI: 10.1016/0749-5978(91)90020-T

Ajzen, I., & Fishbein, M. (1980). *Understanding Attitudes and Predicting Social Behavior*. Englewood Cliffs, NJ: Prentice-Hall.

Al-Jabri, I. M., & Al-Khaldi, M. A. (1997). Effects of user characteristics on computer attitudes among university students. *Journal of End User Computing,* 9(2), 16–22. DOI: 10.4018/joeuc.1997040102

Bandura, A. (1986). *Social Foundations of Thought and Action: A Social Cognitive Theory*. Englewood Cliffs, NJ: Prentice-Hall.

Bandura, A. (1997). *Self-Efficacy: The Exercise of Control*. New York: W. H. Freeman.

Banh, L., & Strobel, G. (2023). Generative artificial intelligence. *Electronic Markets*, 33(1), Article 63.

Barkhordari, M., Nourollah, Z., Mashayekhi, H. et al. (2017). Factors influencing adoption of e-payment systems: An empirical study on Iranian customers. *Information Systems E-Business Management* 15, 89–116. https://doi.org/10.1007/s10257-016-0311-1

Bouteraa, M., Bin-Nashwan, S. A., Al-Daihani, M., Dirie, K. A., Benlahcene, A., Sadallah, M., Zaki, H. O., Lada, S., Ansar, R., Fook, L. M., & Chekima, B. (2024). Understanding the diffusion of AI-generative (ChatGPT) in higher education: Does students' integrity matter? *Computers in Human Behavior Reports, 14*, 100402. https://doi.org/10.1016/j.chbr.2024.100402

Chen, K. & Chang, M. (2013), User acceptance of 'near field communication' mobile phone service: An investigation based on the unified theory of acceptance and use of technology model, *The Services Industries Journal*, 33(6), 609-623.

Chen, A., Downey, J. & Adopo, D. (2023). Usage behaviors of e-payment services by Chinese Millennials (Generation Y) and Zoomers (Generations Z). *Journal of Business Administration Online*, 17(1).

Chen, A., Zeltmann, S., Griffin, K., Ota, M., & Ozeki, R. (2020). Demographic background, perceptions, and e-payment usage among young Japanese. *Global Journal of Business Disciplines*, 4(1), 4-20.

Chopdar, P. K., Korfiatis, N., Sivakumar, V. J., & Lytras, M. D. (2018). Mobile shopping apps adoption and perceived risks: A cross-country perspective utilizing the Unified Theory of Acceptance and Use of Technology. *Computers in Human Behavior*, 86, 109–128. DOI: 10.1016/j.chb.2018.04.017

Compeau, D. R., & Higgins, C. A. (1995). Application of Social Cognitive Theory to training for computer skills. *Information Systems Research*, 6, 118-143. https://doi.org/10.1287/isre.6.2.118

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 13(3), 319–340. DOI: 10.2307/24900.

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User acceptance of computer technology: A comparison of two theoretical models. *Management Science, 35*(8), 982–1003. DOI: 10.1287/mnsc.35.8.982

Downey, J. P., & Rainer, R. K. (2007). Learning outcomes of the information technology end-user: A study of computer self-efficacy. *Journal of Information Systems Education*, 18(4), 403–410.

Downey, J. P., & Smith, L. A. (2011). The role of computer attitudes in enhancing computer competence in training. *Journal of Organizational and End User Computing*, 23(3), 81–100.

Duarte, F. (2024). Number of ChatGPT users. *Exploding Topics*. https://explodingtopics.com/blog/chatgpt-users

Edgell, R. A. (2024). A monstrous matter: The three faces of artificial creativity. *Journal of Creativity*, 34(1), 100075.

Fishbein, M., & Ajzen, I. (1975). *Belief, Attitude, Intention, and Behavior: An Introduction to Theory and Research*. Reading, MA: Addison-Wesley.

Flavián, C., Pérez-Rueda, A., Belanche, D., & Casaló, L. V. (2022). Intention to use analytical artificial intelligence (AI) in services – the effect of technology readiness and awareness. *Journal of Service Management*, 33(2), 293–320.

Gefen, D. (2000). E-Commerce: The role of familiarity and trust. *Omega: The International Journal of Management Science*, 28(6), 725-737.

Gefen, D., Karahanna, E., & Straub, D. W. (2003). Trust and TAM in online shopping: An integrated model. *MIS Quarterly*, 27(1), 51–90. DOI: 10.2307/30036519

Habib, S., Vogel, T., Anli, X., & Thorne, E. (2024). How does generative artificial intelligence impact student creativity? *Journal of Creativity*, 34(1), 100072.

Hu, K. (2023). ChatGPT sets record for fastest-growing user base – analyst note. Reuters. https://www.reuters.com/technology/chatgpt-sets-record-fastest-growing-user-base-analyst-note-2023-02-01/

Immanuel, D. & Dewi, Y. (2020). Mobile payment adoption intention during pandemic covid-19 in Indonesia. *Journal of Information System and Technology Management*, 5(19), 60-76.

Kallanmarthodi, G., & Vaithiyanathan, M. (2012). Assessment of a modified technology acceptance model among E-banking customers in Coimbatore City. *International Journal of Innovation, Management and Technology*, April, 3(2).

Karomah, K., Suroso, A. & Novandari, W. (2021). Factors affecting e-wallet usage intention during covid-19 outbreak in Indonesia. *International Journal of Arts, Humanities, and Social Sciences Studies*, 6(6), 39-51.

Loyd, B. H., & Gressard, C. (1984). The effects of sex, age, and computer experience on computer attitudes. *AEDS Journal*, 18(2), 67–77. DOI: 10.1080/00011084.1984.11008439

Maican, C., Sumedrea, S., Tecau, A., Ciobanu, E., Chitu, I., Radu, L., & Brătucu, G. (2023). Factors influencing the behavioural intention to use AI-generated images in business: A UTAUT2 perspective with moderators. *Journal of Organizational and End User Computing*. 35. 1-32. 10.4018/JOEUC.330019.

Marakas, G. M., Yi, M. Y., & Johnson, R. D. (1998). The multilevel and multifaceted character of computer self-efficacy: Toward clarification of the construct and an integrative framework for research. *Information Systems Research*, 9(2), 126–163. DOI: 10.1287/isre.9.2.126

Nadler, S., Chen, A., & Lin, S. (2019). E-payment usage among urban Chinese. *Journal of Business Diversity*, 19(3), 75-88.

Ortiz de Guinea, A. & Markus, M. (2009). Why break the habit of a lifetime? Rethinking the roles of intention, habit, and emotion in continuing information technology use. *Management Information Systems Quarterly*, 33(3), 433-444.

Polyportis, A. (2024). A longitudinal study on artificial intelligence adoption: understanding the drivers of ChatGPT usage behavior change in higher education. *Frontiers in Artificial Intelligence*, 6., 1-10. https://doi.org/10.3389/frai.2023.1324398

Polyportis, A., & Pahos, N. (2024). Navigating the perils of artificial intelligence: A focused review on ChatGPT and responsible research and innovation. *Humanities and Social Sciences Communications*, 11(1), Article 107.

Popenici, S. A. D., & Kerr, S. (2017). Exploring the impact of artificial intelligence on teaching and learning in higher education. *Research and Practice in Technology Enhanced Learning*, 12(1). https://doi.org/10.1186/s41039-017-0062-8

Rogers, E. M. (1962). *Diffusion of Innovations*. New York: Free Press.

Rogers, E. M. (2003). *Diffusion of Innovations* (5th ed.). New York: Free Press.

Russell, S. J., & Norvig, P. (2010). *Artificial Intelligence: A Modern Approach (3rd ed.)*. Upper Saddle River, NJ: Prentice Hall.

Sudaryanto, M. R., Hendrawan, M. A., & Andrian, T. (2023). The effect of technology readiness, digital competence, perceived usefulness, and ease of use on accounting students artificial intelligence technology adoption. *E3S Web of Conferences*, *388*, 04055. https://doi.org/10.1051/e3sconf/202338804055

Teoh, W., Chong, S., Lin, B., & Chua, J. (2013). Factors affecting consumers' perception of electronic payment: an empirical analysis. *Internet Research*, 23(4), 465-485.

Thatcher, J. B., & Perrewe, P. L. (2002). An empirical examination of individual traits as antecedents to computer anxiety and computer self-efficacy. *MIS Quarterly*, 26(4), 381–396. DOI: 10.2307/4132314

Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the Technology Acceptance Model: Four longitudinal field studies. *Management Science, 46*(2), 186–204.

Venkatesh, V., & Morris, M. G. (2000). Why don't men ever stop to ask for directions? Gender, social influence, and their role in technology acceptance and usage behavior. *MIS Quarterly*, 24(1), 115–139. DOI: 10.2307/3250981

Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the Unified Theory of Acceptance and Use of Technology. *MIS Quarterly*, 36(1), 157–178. DOI: 10.2307/41410412

Wang, Y., Liu, C., & Tu, Y.-F. (2021). Factors affecting the adoption of AI-based applications in higher education. *Educational Technology & Society*, 24(3), 116–129.

Wu, X. & Kuang, W. (2021). Exploring influence factors of WeChat users' health information sharing behavior: based on an integrated model of TPD, UGT, and SCT. *International Journal of Human-Computer Interaction*, 37:13, 1243-1255.

APPENDICES

Appendix A. Survey items

Usage measures:

On average, how frequently do you use ChatGPT or similar tools?

_____Never _____A few times a week

_____About once month _____About once a day

_____A few times a month _____Several times a day

_____About once a week

In an average WEEK, how much time do you spend using ChatGPT or similar tools?

_____No time at all _____5 - 6 hours

_____Less than 1 hour _____7 - 8 hours

_____1- 2 hours _____9 - 10 hours

_____3 - 4 hours _____10+ hours

Motivating variables:

The following measures use a 7-point Likert scale as follows:

1. Completely disagree 5. Somewhat agree

2. Disagree 6. Agree

3. Somewhat disagree 7. Completely agree

4. Either agree or disagree

Note: items lined out were eliminated after factor analyses

Perceived usefulness (PU):

1. AI tools make it easier to fulfill business at work or school
2. AI tools eliminates some time constraints giving me more free time
3. AI tools are useful in my life
4. AI tools will increase my efficiency
5. AI tools will increase my productivity

Perceived ease of use (PEOU):

1. Learning to use AI tools is easy for me
2. I find AI tools to be flexible to interact with
3. My interaction with AI tools is clear and understandable
4. It would be easy for me to become skillful at using AI tools

5. I find AI tools easy to use

Perceived trust (PT):

1. I trust that AI tools will provide accurate information/text
2. I trust that AI tools will not include false information or data
3. I trust AI tools' parent companies
4. I trust that AI tools will have an output that is reasonable and compelling

Perceived risk (PR):

1. Using AI tools is somewhat risky
2. I worry that using AI tools would get me in trouble
3. I am concerned that using AI tools would reflect poorly on me
4. I would feel troubled turning in AI output as my own
5. It would bother me to use AI tools school or work

Anxiety (ANX):

1. AI tools do not scare me at all (reversed scored)
2. Working with AI tools would make me very nervous
3. I do not feel threatened when others talk about AI tools (reversed scored)
4. AI tools make me feel uncomfortable
5. I get a sinking feeling when I think of trying to use AI tools
6. I would feel comfortable working with AI tools (reversed scored)

Positive affect (PAFF):

1. I like working with AI tools
2. I think working with AI tools is enjoyable and stimulating
3. I don't understand how some people can spend so much time working with AI tools and seem to enjoy it (reversed scored)
4. Once I start to work with the AI tools, I find it hard to stop
5. I will do as much work with AI tools as possible
6. I do enjoy talking with others about AI tools

Social influence (SI):

1. People who influence my behavior think I should use AI tools
2. People who are important to me think I should use AI tools
3. Most people around me use AI tools

4. My peers use AI tools

Computer self-efficacy:

Range from 1 (Not at all confident) to 7 (Totally confident). Items 1-6 start with the following:

I could complete a school, work or personal project using an AI tool:

1. …if there was no one around to tell me what to do as I go
2. …if I had never used an AI tool like it before
3. …if I had seen someone else using the AI tool before me
4. …if I could call someone for help if I got stuck
5. …if someone else had helped me get started
6. …if I had a lot of time to complete the job for which the AI tool was used
7. I am confident in my ability to use AI tools
8. Using AI tools is pretty simple
9. AI tools are easy for me to use

Appendix B. Correlation matrix among variables

	Freq	**Dur**	**PU**	**PEOU**	**PT**	**PR**	**ANX**	**PAFF**	**SI**	**CSE**	**Gender**
Frequency	**1**										
Duration	.83**	**1**									
PU	.63**	.54**	**1**								
PEOU	.55**	.45**	.61**	**1**							
PT	.50**	.44**	.64**	.51**	**1**						
PR	-.41**	-.31**	-.42**	-.25**	-.35**	**1**					
ANX	-.50**	-.38**	-.39**	-.54**	-.39**	.59**	**1**				
PAFF	.67**	.60**	.71**	.59**	.72**	-.44**	-.55**	**1**			
SI	.39**	.42**	.44**	.34**	.38**	-.21**	-.18**	.49**	**1**		
CSE	.39**	.32**	.63**	.63**	.30**	-.27**	-.36**	.40**	.30**	**1**	
Gender	-.25**	-.15**	-.27**	-.17**	-.16**	.23**	.34**	-.26**	-.12*	-.21*	**1**
Age	.04	.09	.10	-.07	.04	-.19**	.04	.17**	.20**	.04	01.
Pearson correlations. ** p < .01 * p < .05											