Why Do University Students Use AI: Drivers and Barriers?

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Submitted:
September 8, 2026
Revised:
October 3, 2026
Accepted:
October 17, 2026
Published:
November 2, 2026

Citation:
Chen, A., Ming, L., & Weng, A. (2026). Why University Students Use AI: Drivers and Barriers? *Journal of Higher Education Theory and Practice*, *26*(5), 43–62.

As generative artificial intelligence becomes integrated into academic life, understanding what drives student adoption is essential for informed institutional policy. This study examines AI engagement among 672 students at a public midsize southern university, integrating the Technology Acceptance Model (TAM) and Social Cognitive Theory (SCT) to evaluate eight constructs: perceived usefulness, perceived ease of use, perceived trust, perceived risk, social influence, self-efficacy, anxiousness, and affection. Survey data show students frequently use AI for information retrieval and writing assistance, while specialized applications such as graphic and video generation remain underutilized. Regression analysis shows perceived usefulness, affection, and trust are the primary positive predictors of adoption, whereas anxiety and perceived risk are significant deterrents. Notably, affection, the emotional enjoyment of technology, emerged as one of the most consistent motivators across academic tasks, from research to creative ideation. These results suggest emotional and trust-based factors are as critical as functional utility in shaping student behavior. Universities should prioritize emotional comfort and ethical trust alongside technical training to foster responsible, confident AI integration..

Keywords: artificial intelligence, Technology Acceptance Model (TAM), Social Cognitive Theory (SCT), higher education, technology adoption, student behavior

INTRODUCTION

Beyond its theoretical contributions, this study carries meaningful implications for both the development of AI technologies and the future of college education. As generative AI platforms continue to evolve,

developers and designers must understand the psychological and behavioral profiles of their end users—particularly students, who represent one of the largest and most active user segments. The finding that affection and perceived trust are among the most consistent predictors of AI adoption suggests that future AI development should prioritize intuitive, emotionally engaging, and transparent design over mere functional sophistication. As Schnall et al. (2016) emphasized, "user-centered design and emotional comfort are crucial for encouraging consistent technology usage, especially in education and health contexts" (p. 244). From an educational standpoint, the study underscores the urgent need for universities to move beyond passive AI policies toward proactive, structured AI literacy programs that address both the technical and emotional dimensions of student engagement. Shahzad et al. (2024) similarly found that trust functioned as a cornerstone in ChatGPT acceptance in higher education, reinforcing the idea that institutional credibility and ethical transparency are non-negotiable components of responsible AI integration. Moreover, the identification of anxiety and perceived risk as significant deterrents signals that colleges must create psychologically safe environments where students feel empowered—rather than intimidated—by AI tools (Kwak et al., 2022; Compeau & Higgins, 1995). Taken together, these findings call for a collaborative effort among AI developers, educators, and policymakers to ensure that the next generation of AI tools is not only powerful but also accessible, trustworthy, and pedagogically sound.

The significance of this study lies in its timely and contextually grounded contribution to the rapidly evolving literature on AI adoption in higher education. While prior research has examined technology acceptance among faculty and professional populations (Fathema, 2015; Shata & Hartley, 2025), fewer studies have focused on the lived experiences of undergraduate students at public, mid-sized regional universities—institutions that serve the majority of American college students yet remain underrepresented in educational technology research. By integrating the Technology Acceptance Model (TAM) and Social Cognitive Theory (SCT), this study moves beyond cognitive predictors alone to capture the emotional, social, and trust-based dimensions that shape how students actually engage with generative AI tools. As Awal and Haque (2025) demonstrated, combining perceived usefulness from TAM with self-efficacy from SCT "provided a more holistic explanation of AI chatbot adoption among university students" (p. 596). Furthermore, the study's findings that affection and perceived trust are as consequential as functional utility challenge institutions to rethink AI integration strategies that have historically prioritized technical training over emotional readiness. In an era when tools such as ChatGPT are increasingly woven into academic life, understanding what drives—and deters—student adoption is not merely an academic exercise but an institutional imperative (Davis, 1989; Venkatesh et al., 2003).

Artificial intelligence (AI) has rapidly transformed the educational landscape, offering tools that enhance learning efficiency, personalization, and access to information. The growing ubiquity of generative AI platforms like ChatGPT, Microsoft Copilot, and other large language models has opened new avenues for academic productivity. These technologies help students summarize texts, generate study materials, brainstorm ideas, and even automate administrative tasks. However, while AI holds transformative potential, its integration into academic institutions raises critical questions regarding adoption, accessibility, and equity. At Public Midsize Southern University, students' engagement with AI has grown across academic disciplines.

Preliminary survey data from over six hundred university students reveal varied patterns of AI usage, frequency, and perceived impact on academic tasks. Despite this growing trend, there remains limited scholarly research examining the drivers and deterrents of AI adoption within this institutional context. Specifically, how students perceive AI's usefulness, ease of use, risks, and the influence of their peers remains underexplored. This study investigates the psychological and behavioral determinants of AI usage among students by integrating two well-established theoretical models: the Technology Acceptance Model (TAM) and Social Cognitive Theory (SCT).

The purpose of this research is to (1) measure the extent and type of AI usage among university students, (2) examine the relationship between individual and social factors on AI adoption, and (3) determine how TAM and SCT variables jointly predict the frequency and purpose of AI engagement. This dual-framework approach allows for a multidimensional understanding of AI adoption within higher education.

This study contributes to a growing body of literature on educational technology adoption by addressing these aims. The findings will inform institutional strategies for implementing AI training, support services, and ethical guidelines. In doing so, universities and other higher education institutions can better leverage AI as a tool for academic empowerment, while mitigating risks related to misuse, overreliance, and digital inequality.

This paper is organized into five main sections. The introduction outlines the research context, objectives, and guiding theoretical frameworks. The literature review synthesizes prior studies on AI adoption and establishes the foundation for the proposed hypotheses. The methodology, results, and discussion sections then detail the research design, present the key findings, and interpret their theoretical and practical implications.

LITERATURE REVIEW

The Technology Acceptance Model (TAM) and Social Cognitive Theory (SCT) have been widely used to explain technology adoption in educational environments. TAM, developed by Davis (1989), posits that those two cognitive beliefs—Perceived Usefulness (PU) and Perceived Ease of Use (EU)—are primary predictors of an individual's intention to adopt technology. These constructs have been tested in numerous educational studies and found to affect students' and faculty members' adoption behaviors significantly. For example, El-Gayar, Moran, and Hawkes (2011) found that PU and EU explained a significant portion of student intention to adopt tablet PCs in a Midwestern university, validating the TAM framework in academic technology settings. Likewise, Fathema et al. (2015) extended TAM to faculty usage of learning management systems (LMS), reinforcing the model's utility in understanding instructional technology adoption.

Social Cognitive Theory, introduced by Bandura and later applied to information systems by Compeau and Higgins (1995), focuses on the importance of self-efficacy (SE), outcome expectations, affect, and social influence. SCT has been especially useful in exploring how internal and external perceptions influence behavioral intention. For example, Holden and Rada (2011) showed that K–12 teachers' technology self-efficacy was a stronger predictor of classroom technology usage than general computer self-confidence, supporting the significance of domain-specific self-efficacy. More recently, Shata and Hartley (2025) integrated TAM and SCT to explore generative AI adoption among U.S. faculty. Their findings indicated that PU and social reinforcement were the strongest predictors of faculty intent to adopt AI tools like ChatGPT.

While the Technology Acceptance Model (TAM) has proven effective in quantifying cognitive predictors such as perceived usefulness (PU) and perceived ease of use (PEOU) (Davis, 1989), it has been critiqued for overlooking emotional and contextual factors like trust, anxiety, and social influence (Saadé & Kira, 2006). In contrast, Social Cognitive Theory (SCT) provides a broader perspective by incorporating social and psychological components such as self-efficacy, outcome expectations, and affect (Bandura, 1991; Compeau & Higgins, 1995). However, SCT-based studies often lack TAM's quantifiable precision and simplicity, as the broader scope of variables can be more complex to measure and interpret (Awal & Haque, 2025). Furthermore, while both models have individually been applied to educational technology, studies integrating TAM and SCT, particularly in the context of generative AI adoption in higher education, remain limited (Shata & Hartley, 2025).

A valuable contribution of this study is its focus on a demographic often underrepresented in TAM-based research. While many prior studies have examined professional or faculty populations (e.g., Fathema, 2015; Shata & Hartley, 2025), fewer have explored the perspectives of diverse undergraduate students at public institutions. This focus is important, as students bring distinct experiences, digital fluency levels, and motivations that shape how they engage with AI tools in academic settings.

This study employs TAM and SCT as complementary frameworks to investigate AI adoption. TAM provides the cognitive dimension, measuring beliefs about the usefulness and usability of AI tools. SCT adds a socio-psychological layer, incorporating self-efficacy, anxiety, and social influence. Venkatesh et

al. (2003) support integrating eight models, proposing the Unified Theory of Acceptance and Use of Technology (UTAUT), which draws heavily from TAM, SCT, and other prominent models.

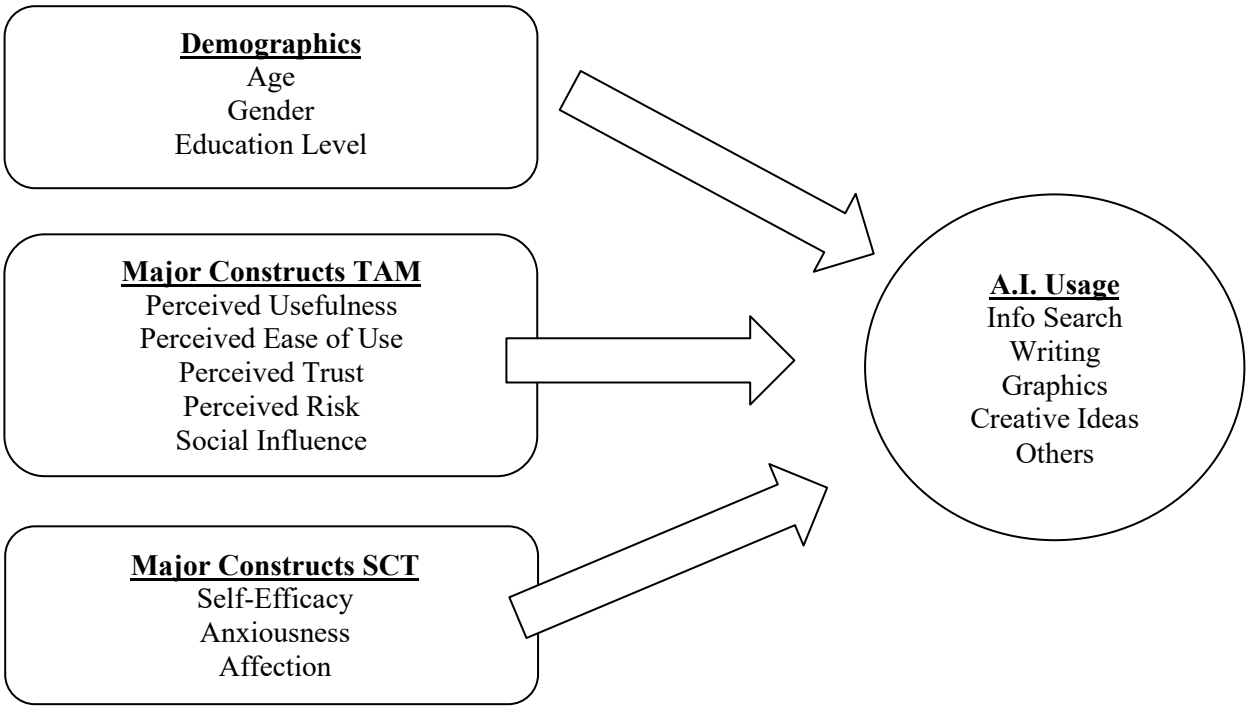
As AI platforms like ChatGPT become more common in academic settings, there is a growing opportunity to understand better how cognitive and social factors shape student adoption. This study contributes to that effort by applying an integrated TAM and SCT framework to explore AI usage among students at a mid-sized, public university in the southern United States. This context has received limited attention in existing research. The study highlights the unique factors that drive AI engagement in diverse learning environments by examining key constructs such as perceived usefulness, self-efficacy, anxiety, and social influence alongside student demographics. These findings offer practical guidance for developing inclusive digital literacy strategies and institutional policies that promote confident and responsible AI use in higher education.

Given the complementary strengths of TAM and SCT, several scholars have emphasized the value of integrating these frameworks to explain the adoption of emerging technologies. Awal and Haque (2025) demonstrated that combining perceived usefulness from TAM with self-efficacy from SCT provided a more holistic explanation of AI chatbot adoption among university students. Similarly, Shata and Hartley (2025) found that generative AI usage in higher education was significantly influenced by both affective engagement and social influence, constructs rooted in SCT and TAM extensions. These insights align with Schnall et al. (2016), who stressed that user-centered design and emotional comfort are crucial for encouraging consistent technology usage, especially in education and health contexts.

By aligning TAM's rational constructs—such as perceived usefulness, ease of use, and trust—with SCT's emotional and behavioral components—like self-efficacy, affection, and anxiety—this study captures both the instrumental and experiential dimensions of AI adoption. For instance, Kwak et al. (2022) found that students' emotional responses and confidence levels were strong predictors of their intent to use AI tools in clinical education. Likewise, Saif et al. (2024) validated that when AI platforms are perceived as intuitive and supportive, adoption increases, especially among learners using ubiquitous platforms like ChatGPT. These findings support the inclusion of emotional and trust-based extensions in traditional technology adoption models.

The following conceptual model (Figure 1) synthesizes these theoretical constructs to illustrate how they jointly influence AI engagement among university students. The framework includes eight core variables and incorporates key demographic factors—such as age, gender, and educational background—as potential moderators. As universities grapple with the ethical, emotional, and practical implications of student AI use, this model offers a multidimensional lens for understanding the psychological and contextual forces shaping adoption. It also serves as the foundation for the subsequent survey design and analysis presented in this study.

FIGURE 1
THEORETICAL FRAMEWORK OF THIS STUDY



HYPOTHESIS DEVELOPMENT

H1: Perceived Usefulness Has a Positive Effect on the Way University Students Use AI

Perceived Usefulness

Perceived usefulness is the degree to which a person believes that using a particular system would enhance job performance (Davis, 1989). In this context, perceived usefulness refers to the degree to which students believe using AI tools enhances their academic performance and productivity. Several studies affirm this; for instance, Sadriwala and Sadriwala (2022) found that PU was a primary motivator for adopting AI technologies in professional contexts, particularly due to its innovation potential. PU significantly influenced students' willingness to engage with e-learning platforms, reinforcing its value in academic adoption decisions. The Technology Acceptance Model (TAM) suggests that usefulness is a primary determinant of technology adoption (Davis, 1989). Usefulness significantly influences user attitudes and behavioral intentions toward AI. Hence:

H2: Perceived Ease of Use Has a Positive Effect on the Way University Students Use AI

Perceived Ease of Use

Perceived ease of use is the degree to which a person believes that using a particular system would be free of effort (Davis, 1989). In this context, perceived ease of use refers to the extent to which students believe that AI tools are intuitive and straightforward, regardless of the task being performed. Schnall et al. (2016) show that ease of use facilitates both trust and utility perceptions. Similarly, Saif et al. (2024) also demonstrated that when AI platforms like ChatGPT are intuitive and require minimal training, students are more inclined to use them consistently for learning tasks. Almogren and Aljammaz (2022) similarly found that ease of use played a central role in mobile learning acceptance, with strong links to user satisfaction and continued use. Students who find it easy to generate outlines, conduct research, or summarize content with AI are more likely to continue using these tools. Hence:

H3: Social Influence Has a Positive Effect on the Way University Students Use AI

Social Influence

Social influence is the degree of susceptibility to suggestion through interpersonal relationships that affects an individual's attitudes, perceptions, and beliefs. This construct has consistently been found to influence behavioral intention. Fathema et al. (2015) found that faculty were more likely to use LMS platforms when colleagues encouraged them. Similarly, Shata and Hartley (2025) found that peer encouragement and academic norms significantly influence faculty and student adoption of educational technologies, including AI. Hence, we propose the following hypothesis:

H4: Perceived Trust Has a Positive Effect on the Way AI is Used Among University Students

Perceived Trust

Perceived trust refers to the extent to which students believe that AI tools are secure, reliable, and will function as intended without introducing academic or ethical harm. Trust has emerged as a critical extension of TAM in recent AI-focused studies. Schnall et al. (2016) and Rajak and Shaw (2021) found that trust was vital for adopting digital platforms in health and mobile contexts. Shata and Hartley (2025) noted that trust mediated the effect of ease of use on intention to adopt ChatGPT in academic environments. Therefore:

H5: Perceived Risk Harms the Way AI Is Used Among University Students

Perceived Risk

Perceived risk is "a combination of uncertainty about a product or service, plus the seriousness of the outcome involved" in its usage (Bauer, 1960). Perceived risk is commonly considered uncertainty regarding possible negative consequences of using a product or service (Featherman & Pavlou, 2003). In studies by Rajak and Shaw (2021), risk emerged as a strong deterrent to engagement with AI platforms, especially when academic performance or integrity was at stake. Hence:

H6: Self-Efficacy Has a Positive Effect on the Way University Students Use AI

Self-Efficacy

Self-efficacy is defined as people's beliefs about their capabilities to exercise control over their level of functioning and over events that affect their lives (Bandura, 1991). Social Cognitive Theory (SCT) places self-efficacy at the core of behavioral motivation. Compeau and Higgins (1995) developed a computer-specific self-efficacy measure, while their follow-up study (Compeau et al., 1999) demonstrated that self-efficacy positively affects computer usage and attitudes. In a recent study, Kwak et al. (2022) confirmed that higher AI-related self-efficacy predicted students' likelihood of using AI in clinical training. Thus:

H7: **Affection Has a Positive Effect on the Way AI Is Used Among University Students**

Affect

Affect is an individual's liking for a particular behavior (Venkatesh et al., 2003). Venkatesh et al. (2003) integrated affective responses into TAM extensions via the concept of hedonic motivation. Enjoyment and emotional satisfaction can drive sustained technology use, especially when learning tasks are repetitive or cognitively demanding. Kwak et al. (2022) also identified emotional comfort with AI tools as a significant predictor of intention to use. Thus:

H8: **Anxiety Has a Negative Effect on the Way AI Is Used Among University Students**

Anxiety

Anxiety refers to evoking anxious or emotional reactions when it comes to performing a behavior (Venkatesh et al., 2003). In this context, it refers to apprehension or unease about using AI in an academic or school setting. This emotional barrier has been recognized in SCT as a key inhibitor of technology usage (Compeau & Higgins, 1995). Holden and Rada (2011) showed that anxiety could suppress teachers' willingness to experiment with new digital platforms. Similarly, Kwak et al. (2022) reported that students with higher AI-related anxiety were less likely to adopt such tools in their educational routines. Hence:

METHODOLOGY

The sample consisted of 672 undergraduate and graduate students enrolled in a State University in the South. Participants represented various majors, class standings, and demographic backgrounds. The survey was distributed campus-wide, ensuring voluntary participation and anonymity. No identifying information was collected, and Institutional Review Board (IRB) approval was obtained before data collection.

The survey instrument included items adapted from validated scales in prior research. Questions measuring perceived usefulness, perceived ease of use, and social influence were adapted from Davis (1989) and Venkatesh et al. (2003). Items related to perceived trust and perceived risk were adapted from scales by Gefen et al. (2003) and Featherman and Pavlou (2003), while questions on self-efficacy, affection, and anxiety were adapted from Compeau and Higgins (1995) and Venkatesh et al. (2012). All items were modified to fit the context of student AI usage in academic settings. Each construct, perceived usefulness, perceived ease of use, social influence, self-efficacy, affection, anxiety, perceived trust, and perceived risk, was measured using multiple items on a 7-point Likert scale ranging from 1 ("Strongly Disagree") to 7 ("Strongly Agree"). Reliability analyses confirmed internal consistency for most scales, with Cronbach's alpha values exceeding .70 for all constructs except anxiety.

In addition, students were asked about the frequency and types of AI use, including tasks such as information search, writing assistance, creative idea generation, and media creation. Data were collected using an online survey administered through Qualtrics. The survey link was disseminated via university email and student organizations. Respondents were required to give informed consent prior to beginning the survey. The data collection period lasted four weeks via the Qualtrics platform. Following the collection, the data were cleaned and analyzed using SPSS. Analyses included descriptive statistics, reliability testing (Cronbach's alpha), Pearson correlations, and multiple regression models to evaluate the influence of each construct on specific types of AI tool usage.

In the following section, we will examine the demographic background of respondents. The sample includes 672 participants, with females making up the majority at 53.4%, and males accounting for 37.6%. A small fraction of participants identified as "Other" (1.5%) or preferred not to specify (1.5%). The mean of 0.59 (standard deviation 0.49) for gender likely reflects binary coding (e.g., 0 = male, 1 = female), indicating a slight overrepresentation of females. Approximately 6% of responses were missing, a typical survey-based research rate.

Participants were predominantly traditional college-aged students, with 38.5% aged 20–29 and 33.5% aged 16–19. Only 8.1% of the sample reported being 30 or older, and 19.8% of respondents did not provide their age. The mean age was 22.58 years, with a standard deviation of 8.14, indicating moderate dispersion and skewing toward younger ages. This reflects a typical undergraduate-heavy population suitable for generalizing findings to traditional student demographics.

In terms of academic level, the largest group was freshmen (34.1%), followed by seniors (19.5%), juniors (15.5%), and sophomores (14.7%). Graduate students represented 9.8%, with non-degree-seeking students comprising only 0.4%. The class level had a mean value of 2.53 and a standard deviation of 1.42, indicating a reasonably even distribution across undergraduate class years. The asterisk next to "15.53" likely refers to a derived measure from reported educational attainment in years, helping to explain educational progression in a numeric format.

More than half of the students (50.9%) were from the College of Business, likely reflecting the recruitment source. Other colleges represented include Arts, Humanities, and Social Sciences (15.2%), Health & Behavioral Sciences (11.5%), Natural Sciences & Mathematics (10.6%), and Education (4.9%). The mean and standard deviation are not applicable (N/A) for this categorical variable, as no numeric scale is assigned to college affiliation.

A substantial portion of students (31.0%) reported not working, while 21.3% worked 11-20 hours and 15.9% worked 1-10 hours weekly. Fewer students worked more than 30 hours; only 0.3% exceeded 60 hours per week. The mean number of work hours was 13.21, with a standard deviation of 14.02, indicating substantial variation in work commitments. These data suggest that many students balance part-time employment alongside their studies.

More than half of students (55.4%) studied 1–10 hours per week, and another 25.6% studied 11–20 hours. The mean study time was 10.71 hours per week, with a standard deviation of 9.18, suggesting moderate variability in academic effort. A small number reported very high study commitments, and 6% of responses were missing, consistent with other variables.

Income data reveal that 41.4% of students earn $1–$1,000 per month, and 24.7% report no income. Only 13.5% earn between $1,001–$2,000, and even fewer earn higher amounts. The mean monthly income was estimated at $1,225.04, with a very high standard deviation of $2,300.64, based on midpoints of income brackets. This wide variability suggests economic diversity among students, with implications for access to paid AI tools and digital resources.

Table 1 provides a comprehensive demographic profile of university students participating in the study. The sample comprises traditionally aged undergraduates, with a significant proportion from the College of Business. Most students report modest income levels and work part-time, with typical study loads. These characteristics underscore the importance of designing AI tools that are accessible, time-efficient, and adaptable to varying academic and economic circumstances. The demographic spread also supports analyses that examine how factors like age, class standing, and income moderate AI adoption behaviors in educational settings.

TABLE 1
DESCRIPTIVE STATISTICS FOR DEMOGRAPHIC VARIABLES

Gender	**Frequency**	**Percent**	**Mean**	**S.D.**
Male	253	37.6	.59	.49
Female	359	53.4		
Would rather not specify	10	1.5		
Other	10	1.5		
Missing	40	6.0		
Total	672	100.0		
Age				
16-19	225	33.5	1.78	.91
20-29	259	38.5	22.58**	8.14**
30-39	23	3.4		
40-49	20	3.0		
50-59	7	1.0		
60+	5	.7		
Missing	133	19.8		
Total	672	100.0		
Class				
Freshman	229	34.1	2.53	1.42
Sophomore	99	14.7	15.53*	1.42*
Junior	104	15.5		
Senior	131	19.5		
Graduate	66	9.8		
Non-degree-seeking students	3	.4		
Missing	40	6.0		
Total	672	100.0		

* Uses Edu which calculates # of Years of education completed
** Mean and Standard Deviation using the mid-value of the range

Cronbach's alpha is a statistical measure used to assess the internal consistency or reliability of a set of scale or test items. It tells us how well a group of items measures a single unidimensional latent construct. A high Cronbach's alpha (typically ≥ 0.70) indicates that the items are well-correlated and consistently reflect the same underlying concept. This makes it a crucial diagnostic for validating multi-item survey instruments in social science and behavioral research.

In this context, all the constructs measured in Table 2 exhibit Cronbach's alpha values above 0.80, which signifies strong reliability. Constructs such as *Perceived Usefulness (PU)* and *Ease of Use (EU)* show exceptionally high reliability ($\alpha = 0.95$). At the same time, even the lowest value, for *Anxiety (AX)* at 0.83, still surpasses the acceptable threshold, suggesting sound scale construction across all constructs.

Table 2 presents the Cronbach's alpha coefficients, number of items, and descriptive statistics (mean and standard deviation) for nine primary psychological and behavioral constructs associated with AI adoption among university students. Perceived Usefulness (PU) and Perceived Ease of Use (EU) have alpha values of 0.95, reflecting excellent internal reliability. Their means are 4.64 and 4.93, respectively, suggesting that students generally view AI as beneficial and easy to use in academic contexts. The relatively high standard deviations (1.63 and 1.39) indicate varied responses but a strong central tendency toward agreement.

Perceived Trust (PT) has a slightly lower mean (3.37) and an alpha of 0.92, suggesting that while the construct is measured reliably, students are more neutral or divided in their trust toward AI technologies. Perceived Risk (PR) has a mean of 4.92 with an alpha of 0.86, suggesting that students have notable concerns about AI use—perhaps regarding accuracy, ethical use, or academic integrity—even though the measure is internally consistent.

Anxiety (AX) is unique in that it uses a bipolar or reverse-coded scale, resulting in a negative mean of -0.44. Despite this coding, its alpha of 0.83 confirms reliability. The negative value indicates that students, on average, experience low anxiety toward using AI tools. Affect (AF), which gauges students' emotional connection or enjoyment in using AI, has a moderate mean of 3.60 and a strong alpha of 0.88, indicating reliable yet slightly varied sentiment. Social Influence (SI) and Self-Efficacy (SE) are also robust, with alphas of 0.89 and 0.96, respectively. Their means (SI = 4.52, SE = 4.56) indicate that peers positively influence students and feel confident in their ability to use AI.

Lastly, USAGE, which measures the frequency and depth of AI use behavior, shows a mean of 3.25 and an alpha of 0.89. This suggests that although usage behavior is reliably captured, the mean is lower than the attitudinal constructs, indicating that favorable perceptions do not always translate into consistent usage. Usage is a composite variable. We used the ordinal coding of dependent variables: User AI use self-assessment, frequency of AI tools use, Time spent on AI, and percentage of schoolwork done using AI. The Cronbach's Alpha was found to be .89. We took the average of four ordinal values and made an additional measure of e-payment behavior that consists of all four aspects named "Usage" (see Table 2).

Overall, the reliability of all constructs in Table 2 is statistically strong, reinforcing the validity of the measurement instruments. The descriptive statistics suggest that while students perceive AI positively regarding usefulness, ease of use, and social support, trust and actual usage are more conservative, and risk and anxiety remain relevant deterrents. These patterns are consistent with known adoption behavior dynamics and support further multivariate analysis, such as regression or mediation models, to explore causal relationships.

TABLE 2
CRONBACH ALPHAS AND DESCRIPTIVE ANALYSIS OF MAJOR CONSTRUCTS

	Items	Alpha	Mean	S.D.
Perceived Usefulness (PU)	5	0.95	4.64	1.63
Perceived Ease of Use (EU)	5	0.95	4.93	1.39
Perceived Trust (PT)	4	0.92	3.37	1.38
Perceived Risk (PR)	5	0.86	4.92	1.35
Anxiety (AX)	6	0.83	-.44	1.26
Affect (AF)	5	0.88	3.60	1.35
Social Influence (SI)	10	0.89	4.52	1.06
Self-efficacy (SE)	9	0.96	4.56	1.59

RESULTS

Table 3 presents descriptive statistics on the different types of AI use among university students, measured by mean frequency and standard deviation (S.D.), on a 7-point Likert scale (e.g., from “never” to “very frequently”). This breakdown provides nuanced insights into how students interact with AI tools for academic and creative tasks.

The most frequently reported AI use was information search, with a mean of 3.38 and a standard deviation of 2.1. This suggests that students commonly rely on AI to retrieve and synthesize academic content. This aligns with AI’s role in aiding rapid access to information, much like enhanced search engines. Grammar and spelling support was the second most frequent use, with a mean of 3.27, indicating that AI tools like ChatGPT and Grammarly are widely employed for writing refinement. The similar standard deviation (2.1) shows comparable variability in usage across the sample.

The generation of creative ideas holds a mean of 2.89, showing moderate use. This suggests students are beginning to explore AI for brainstorming and ideation, especially in writing assignments or project planning. The standard deviation of 1.9 indicates a slightly narrower range of use, implying that while some students experiment heavily with creative applications, others are less inclined. "Other uses," such as scheduling assistance, summarizing, or coding, have a mean of 2.39, indicating these are less mainstream but still present in the user experience.

The least utilized AI function is graphics, visuals, and video generation, with a mean of 1.81 and a standard deviation of 1.5. This reflects limited engagement with visual AI tools such as DALL·E or Adobe Firefly, likely due to lower awareness, technical skill requirements, or less curricular integration of visual media tasks. It may also point to a perceived complexity or lack of necessity for multimedia content in most academic work.

These statistics suggest that students predominantly use AI for text-based academic support—searching for information and refining writing—while more advanced or specialized applications like creative ideation and multimedia generation remain underutilized. The data reveals a clear opportunity for expanding AI literacy and training, particularly in creative and visual domains. Educators might consider integrating these broader applications into coursework to enhance digital skills and innovation, ensuring students can fully leverage AI’s diverse capabilities in academic and professional settings.

TABLE 3
DESCRIPTIVE STATISTICS FOR AI USAGE

Types of Usage	Mean	S.D.
Information Search	3.38	2.11
Grammar and Spelling (Writing)	3.27	2.05
Generating Creative Ideas	2.89	1.94
Other Uses	2.39	1.79
Graphics, Visuals, and Videos	1.81	1.51

The following section will analyze the relationship between independent and dependent variables. A Pearson correlation analysis was conducted to show the relationships. Table 4 shows the results for the bivariate analysis. Items 1-3 are demographic variables. Items 4 - 11 are the primary constructs from the Technology Acceptance Model (TAM) and Social Cognitive Theory (SCT). Items 12 - 16 are the different types of AI usage. The results explain how student characteristics and psychological or behavioral factors relate to specific AI behaviors.

Among the demographic variables, age was negatively correlated with most forms of AI usage, particularly information search ($r = –.05$, $p > .05$), writing ($r = –.10$, $p < .05$), and creative ideas ($r = –.07$, $p > .05$), suggesting that younger students were more likely to use AI tools for academic purposes. Gender had weak or non-significant correlations with AI usage. However, education level showed a non-significant negative relationship with information search ($r = -.03$, $p > .05$), indicating that students at higher educational levels may be slightly more likely to use AI for research-related tasks.

The strongest predictors of AI usage were perceived usefulness and affection, which were positively and significantly correlated with all five AI use types. For example, perceived usefulness had moderate to strong correlations with information search ($r = .52$), writing ($r = .39$), and creative idea generation ($r = .39$), all significant at the $p < .01$ level. Similarly, affection was strongly correlated with creative ideas ($r = .49$) and information search ($r = .52$), showing that students who enjoy using AI tend to apply it across multiple academic tasks.

Other variables followed expected patterns: self-efficacy, ease of use, and trust were positively associated with all AI usage types, though correlations were generally moderate. Perceived risk and anxiety, by contrast, were negatively correlated with most usage categories. Anxiety had significant negative correlations with writing ($r = –.26$), creative ideas ($r = –.28$), and information search ($r = –.33$), suggesting that discomfort or fear of using AI may limit how students engage with these tools. These findings further validate the role of emotional and trust-based factors in shaping AI tool adoption and use.

In addition to the core constructs, social influence showed consistent positive correlations across all AI usage types, with the strongest association found with writing tasks ($r = .16$, $p < .01$). This suggests that encouragement or perceived expectations from peers, instructors, or academic culture may influence students to adopt AI tools, particularly for tasks that involve formal or structured output. Although the strength of the correlation was moderate, its consistency across domains implies that the social environment plays a meaningful role in shaping students' willingness to experiment with AI in academic work.

Notably, graphics or visual content generation had the weakest overall correlations with the independent variables, with affection ($r = .35$), trust ($r = .24$), and self-efficacy ($r = .14$) being the most relevant predictors. This may reflect the relatively low usage of AI for visual tasks observed in descriptive results and the possibility that students feel less confident or experienced with using AI for creative design. In contrast, text-based tasks like writing and information search had more substantial and widespread associations across nearly all constructs, reinforcing the idea that AI tools are primarily used as academic assistants rather than creative collaborators. These patterns suggest that while core TAM and SCT variables effectively explain general AI use, their influence may vary by task type, especially in areas requiring higher creativity or design skills.

To deepen the understanding of how the proposed constructs influence different types of AI usage, a Pearson correlation analysis was conducted. While descriptive statistics highlighted the frequency and

variation in usage patterns, correlational analysis provides clarity on the strength and direction of relationships between student characteristics, theoretical constructs, and AI behaviors. This step allows for an initial test of the model's validity before advancing to regression analysis.

Table 4 presents the correlation matrix for all primary variables in the study, including demographic factors (age, education, gender), TAM and SCT constructs, and five specific AI usage types. These correlations help identify which variables are most closely associated with each form of AI engagement. For instance, perceived usefulness and affection exhibit strong positive correlations with tasks like information search and writing, while anxiety and perceived risk show consistent negative relationships across multiple categories.

Analyzing these patterns offers a more nuanced view of AI adoption, revealing that students who enjoy using AI or believe it enhances their performance are more likely to use it frequently and across various academic tasks. Conversely, those with higher anxiety or concerns about risk tend to avoid using AI, particularly in creative or high-stakes contexts. These findings support the theoretical proposition that both cognitive and emotional factors contribute to technology adoption and set the stage for the regression models that follow.

It is important to summarize all constructs with the five types of AI usage. Table 5 presents the results of hypothesis testing across the eight theoretical constructs and five categories of AI usage. All eight constructs were statistically significant in at least one domain, supporting the study's proposed model. Perceived usefulness, affection, and perceived trust emerged as the most consistent positive predictors, especially in tasks such as information search, writing, and creative idea generation. These findings reinforce the core assumptions of the Technology Acceptance Model (TAM) while highlighting the importance of emotional engagement and trust in AI tools. Students who found AI helpful, enjoyable, and trustworthy were more likely to integrate it into their academic workflows.

While Table 5 provides detailed statistical outcomes, its broader significance lies in clarifying the relative weight of each construct across different AI tasks. The consistent predictive power of perceived usefulness, affection, and trust underscores that both rational and emotional factors are central to student adoption. In contrast, variables such as ease of use and self-efficacy become relevant only in specialized contexts, such as graphics or idea generation. Notably, the negative impact of anxiety and perceived risk suggests that emotional barriers are just as influential as technical considerations, signaling to educators that adoption strategies must extend beyond usability improvements. In practice, this means institutions should not only promote AI as a valuable academic tool but also create learning environments that reduce apprehension and cultivate positive student experiences with the technology.

Conversely, anxiety and perceived risk were significant negative predictors across multiple categories. Anxiety was particularly influential in writing and idea generation tasks, suggesting that discomfort or fear of AI errors can discourage use in creative or high-stakes academic areas. Perceived risk was also a notable barrier in less-structured activities, such as graphics and other uses, where students may be more concerned about misinformation or ethical implications. While all constructs contributed to understanding AI use, their effects varied by task type, underscoring the need for a nuanced view of student behavior that accounts for emotional and task-specific factors.

TABLE 4
PEARSON CORRELATION

	Mean	S.D.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1 Age	22.58	8.14	1															
2 Edu	2.53	1.42	.52**	1														
3 Gen	0.59	0.49	.12**	.28**	1													
4 PU	4.64	1.62	0.02	0.03	-0.07	1												
5 EU	4.93	1.39	-0.02	0.03	-0.03	.63**	1											
6 PT	3.37	1.38	-0.07	-.15**	-0.08	.62**	.52**	1										
7 PR	4.92	1.35	-0.07	0.08	.22**	-.19**	0.00	-.15**	1									
8 AF	3.60	1.35	0.01	-0.01	-.10*	.73**	.53**	.65**	-.19**	1								
9 SI	4.52	1.06	-0.02	0.087	0.08	.42**	.43**	.32**	.15**	.44**	1							
10 SE	4.56	1.59	-0.00	0.086	-0.09	.48**	.60**	.29**	-.11*	.41**	.39**	1						
11 AX	-0.44	1.26	-0.01	0.066	.16**	-.58**	-.55**	-.40**	.45**	-.52**	-.12**	-.49**	1					
12 Info Search	3.38	2.11	-0.05	-0.03	-0.07	.52**	.36**	.44**	-.20**	.52**	.30**	.26**	-.33**	1				
13 Writing	3.27	2.04	-.10*	-0.02	0.03	.39**	.25**	.29**	-.19**	.40**	.16**	.21**	-.26**	.42**	1			
14 Graphics	1.81	1.51	0.03	-0.00	-0.05	.19**	.09*	.24**	-.11*	.35**	.16**	.14**	-.14**	.30**	.32**	1		
15 Creative ideas	2.89	1.94	-0.07	-0.05	-0.07	.39**	.23**	.30**	-.17**	.49**	.24**	.31**	-.28**	.40**	.45**	.50**	1	
16 Others	2.39	1.79	-0.09	-0.05	-.10*	.39**	.25**	.30**	-.20**	.47**	.24**	.24**	-.27**	.38**	.40**	.42**	.49**	1

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).

TABLE 5
RESULTS OF HYPOTHESIS TESTING

ATTITUDES	Info Search	Writing	Graphics	Creative Ideas	Others
AF Affection	Accept **	Accept **	Accept **	Accept **	Accept **
EU Ease of Use	Accept **	Accept **	Accept *	Accept **	Accept **
PT Perceived Trust	Accept **	Accept **	Accept **	Accept **	Accept **
PR Perceived Risk	Accept **	Accept **	Accept *	Accept **	Accept **
AX Anxiousness	Accept **	Accept **	Accept **	Accept **	Accept **
PU Perceived Use	Accept **	Accept **	Accept **	Accept **	Accept **
SI Social Influence	Accept **	Accept **	Accept **	Accept **	Accept **
SE Self-efficacy	Accept **	Accept **	Accept **	Accept **	Accept **

Level of significance at the 0.05 level = * and 0.01 level

In the last section, multivariate analysis was conducted. We apply stepwise regression to identify relationships between complications and independent variables. Table 6 presents the results of stepwise regression analysis conducted separately for each AI usage type. Stepwise regression is a statistical technique used to identify the most significant predictors of a dependent variable by systematically adding or removing independent variables based on specific criteria, such as statistical significance (typically p-values). The primary purpose of stepwise regression is to build a parsimonious model that explains as much variance in the outcome as possible with the fewest predictors. This method is beneficial when dealing with a large set of potential predictors, as it helps to isolate the most impactful variables while minimizing overfitting.

Information Search

The regression model for AI use in information search was statistically significant, $F = 67.62$, $p < .001$, with an R^2 of .327, indicating that the model explained approximately 33% of the variance in students' use of AI for searching information. Perceived usefulness was a significant positive predictor; students who believed that AI tools improved their ability to retrieve relevant academic information were more likely to engage in this form of usage. Affection also had a significant positive influence, suggesting that students who enjoyed using AI tools were more inclined to apply them for information-gathering tasks. Additionally, perceived trust emerged as a strong positive predictor, indicating that when students viewed AI platforms as reliable and secure, they were more confident using them to search for academic content. PU, AF, and PT are the three primary constructs that explain information search among university students.

Writing

The regression model for AI use in writing tasks was significant, $F = 52.89$, $p < .001$, with an R^2 of .204, meaning that the predictors explained about 20% of the variance. Perceived usefulness significantly predicted AI use in writing; students who viewed AI tools as helpful for improving the structure or clarity of their writing were more likely to use them in academic writing. Affection was also a significant factor, indicating that students using AI tools enjoyable or satisfying were more willing to incorporate them into their writing processes. The two primary constructs for Writing purposes are PU and AF.

Graphics/Visual Content

The regression model for AI usage related to visual or graphic generation was significant, $F = 28.89$, $p < .001$, with an R^2 of .125, indicating that about 12.5% of the variance was explained. Affection again was a significant positive predictor, meaning that students who enjoyed using AI were more likely to explore visual design features, perhaps driven by curiosity or a preference for aesthetic tasks. Perceived ease of use was negatively related to this type of usage. This may suggest that students with more technical or advanced expectations found the tools overly simplified or less suitable for complex design. Similarly, perceived risk

was a negative predictor, indicating that students concerned about copyright, originality, or the credibility of AI-generated visuals were more hesitant to use these tools for visual academic content. The two primary factors for Graphics and Visual AI are AF and EU.

Creative Ideas

The model predicting AI use for generating creative ideas was statistically significant, $F = 73.06$, $p < .001$, with an R^2 of .262. Affection was the strongest predictor in this model. Students who had positive emotional reactions to using AI were significantly more likely to turn to these tools for brainstorming or idea generation, perhaps because they associated AI with fun, novelty, or inspiration. Self-efficacy also had a significant positive effect: students who felt confident using AI tools effectively were more likely to use them for creative thinking, suggesting that comfort with the tool enables broader and more imaginative applications. Moreover, perceived risk has been identified as the third factor influencing the use of creative ideas. The three primary constructs for Creative Ideas are AF, SE, and PR.

Other Uses

The model for other uses of AI (e.g., summarization, study support, or general task assistance) was also significant, $F = 59.40$, $p < .001$, with an R^2 of .240. Affection was the dominant predictor once again. Students with positive emotional experiences with AI were likelier to experiment with it for various academic support tasks, demonstrating how enjoyment encourages exploratory and flexible use. Perceived risk had a significant adverse effect, suggesting that students who had reservations about AI-generated errors or ethical concerns were less likely to engage with AI tools outside narrowly defined academic functions. The two primary factors for Other AI usage are AF and PR.

TABLE 6
STEP-WISE REGRESSION ANALYSIS

	Info Search		**Writing Tasks**		**Graphics**		**Creative Ideas**		**Others**	
	U.C. B	**t**	**U.C. B**	**t**	**U.C. B**	**t**	**U.C.B**	**t**	**U.C.B**	**t**
Constant	-.348	-1.24	.555	1.94	.853	3.07	-.113	-.39	.901	2.21
PU	.322	4.03**	.314	3.85**						
AF	.374	3.77**	.363	3.65**	.45	7.35**	.655	9.60**	.602	10.06**
PT	.276	3.24**								
EU					-.13	-2.12**				
SE							.149	2.49**		
PR							-.140	-2.161**	-.140	-2.32**
R^2	.327		.204		.125		.262		.240	
F	67.62		52.89		28.89		73.06		59.40	
Sig.	<.001		<.001		<.001		<.001		<.001	

Level of Significance at 0.05 * and 0.01 **
U.C. B = Unstandardized Coefficients B

DISCUSSION

This study explored the behavioral and psychological predictors of AI use among college students, using an integrated Technology Acceptance Model (TAM) and Social Cognitive Theory (SCT) framework, along with extensions such as perceived trust and perceived risk. The results confirmed that constructs such as perceived usefulness, affection, and perceived trust were among the strongest and most consistent predictors of students' AI use across different academic contexts, particularly for information search, writing, and creative ideation. These findings align with Davis (1989), who initially identified perceived usefulness as the central driver of technology acceptance. They extend the model by reinforcing its importance in a modern educational AI setting. Similarly, affection, as conceptualized by Venkatesh et al. (2003) and emphasized by Kwak et al. (2022), emerged as a powerful emotional motivator, indicating that students are more likely to use AI when they enjoy it or feel positively toward it.

Students who viewed AI tools as helpful in improving the quality or efficiency of their academic work were more likely to integrate them into daily study routines, particularly for tasks such as writing, researching, and brainstorming. This finding reinforces the central role of PU in the Technology Acceptance Model (Davis, 1989). It echoes more recent research by Shahzad et al. (2024), which found that usefulness was a key driver in students' acceptance of educational AI platforms like ChatGPT. The emergence of perceived usefulness as a consistent predictor strongly supports H1, which posited a positive relationship between PU and AI usage. Institutions can build on this by emphasizing how AI tools directly support academic success.

Affection, the emotional positivity or enjoyment students associate with using AI tools, was among the most consistent predictors in this study, offering strong support for H7, which hypothesized a positive relationship between affection and AI usage. Students who felt emotionally satisfied with AI were more likely to adopt it for routine and exploratory tasks, including creative ideation and general academic support. This finding aligns with Saadé and Kira's (2006) work, emphasizing that affective responses can directly shape technology adoption. These findings suggest that making AI tools enjoyable and intuitive can boost student engagement. Affection is significant in a university setting for AI usage.

The significant role of perceived trust in predicting AI usage, particularly for tasks like information search, supports prior findings by Schnall et al. (2016) and Rajak and Shaw (2021), who observed that trust fosters greater willingness to adopt digital platforms. Usability and perceived accuracy often mediated trust in AI systems. This echoes our findings: students were more likely to use AI when they viewed it as secure, reliable, and academically appropriate. Promoting transparency, platform credibility, and ethical usage guidelines may be key strategies for increasing trust and facilitating adoption. Students are fully aware that AI-generated results may not be accurate. It is good training for university students because the use of AI and critical thinking are closely related.

Interestingly, perceived ease of use, while theoretically expected to be influential (Davis, 1989; Fathema, 2015), did not consistently predict AI usage across all categories and even had a negative association with graphic usage. This could be due to construct redundancy or conceptual overlap with perceived usefulness and trust, as supported by the strong intercorrelations observed in Table 4. Some of these predictors may have been statistically overshadowed in regression due to multicollinearity. As Schnall et al. (2016) show, ease of use often boosts trust and usefulness simultaneously, making its direct predictive value context-dependent. University students are proficient with computers. Thus, the ease of use is not as significant as it will be for other user groups.

Furthermore, while self-efficacy was strongly correlated with AI use, its effect was statistically significant only for creative idea generation. This supports Bandura's (1991) emphasis on task-specific confidence and mirrors findings by Compeau and Higgins (1995) and Kwak et al. (2022), who found that self-efficacy played a stronger role in tasks requiring greater initiative or experimentation. Notably, although social influence was positively correlated with all types of AI use, it was not a significant predictor in any single task. This outcome contrasts with prior studies, such as Fathema et al. (2015) and Shata and Hartley (2025), which found that peer and institutional norms are crucial to technology adoption. This

discrepancy may be because students in this sample were already familiar with AI tools, suggesting that social cues may be more impactful during early exposure than during continued use.

As expected, perceived risk and anxiety consistently negatively affected AI usage, supporting H5 and H8. These results align with Featherman and Pavlou (2003), who found that concerns about inaccuracy, originality, and ethical implications deterred users from engaging with AI tools. Students may worry about misinformation, academic dishonesty, or technical limitations, which deters deeper engagement. Anxiety, in particular, had the strongest negative correlation with writing and idea generation, suggesting that emotional discomfort may act as a barrier to creative engagement.

Overall, the regression results affirm the utility of TAM-SCT integration for understanding AI behavior in college students, especially when accounting for emotional (affection), trust-based, and risk-related factors. This supports the expanded models proposed by Awal and Haque (2025) and Almogren and Aljammaz (2022), who found that emotional comfort and social-cognitive factors like trust, affect, and self-efficacy play a substantial role in AI acceptance. The findings also highlight that the task type matters: AI adoption for text-heavy or idea-generation purposes is more strongly influenced by enjoyment and trust. In contrast, visual tasks are more sensitive to risk and perceived complexity.

These results offer several theoretical contributions. First, they validate the integration of SCT's affect and self-efficacy dimensions into TAM, providing a richer understanding of student adoption patterns. Second, they demonstrate that emotional engagement and trust are not just peripheral factors, but core predictors of AI use. Finally, they show that TAM variables alone are insufficient, especially in tasks where risk perception or affective responses dominate decision-making.

These findings suggest that institutions should not only focus on training students in the technical use of AI but also build emotional comfort and trust, while actively addressing perceived risks and ethical concerns. Interventions such as AI literacy workshops, ethical use guides, and student support resources could help demystify AI and reduce student anxiety. Future research should replicate this model in other university contexts to examine generalizability and investigate longitudinal patterns of AI engagement.

CONCLUSIONS

This study examined the types of AI usage among college students at a public University in Arkansas. It tested a comprehensive technology adoption model using constructs from the Technology Acceptance Model (TAM), Social Cognitive Theory (SCT), and related extensions such as perceived trust and risk. Findings showed that students predominantly use AI tools for information search, creative ideation, and writing. Constructs such as perceived usefulness, affection, and trust were significant predictors of AI engagement, whereas anxiety and perceived risk were barriers. The study contributes to the growing literature on educational AI by confirming the importance of emotional and social variables alongside traditional cognitive predictors.

Beyond theory, these results have direct implications for educators and institutions. Universities should focus on three practical strategies: (1) building student trust in AI tools by emphasizing reliability, transparency, and ethical guidelines; (2) fostering positive emotional experiences through training that highlights enjoyable, creative, and empowering applications of AI; and (3) mitigating risk and anxiety by providing clear guidance on responsible AI use, academic integrity, and limitations of generative platforms. Incorporating AI literacy programs into curricula, offering workshops, and developing policies that address both practical and ethical concerns can help bridge the gap between adoption and effective use. These actions will allow institutions to not only encourage AI engagement but also prepare students for a future in which AI integration is inevitable.

Based on the results of this study, several directions for future research are evident. First, future studies should examine how faculty or institutional policies influence students' perceived risk and ethical concerns surrounding AI use. Second, longitudinal research could explore how AI usage behaviors evolve as students progress through their academic careers or as AI tools become more embedded in curricula. Third, future work should replicate and extend this study across different university contexts—both in terms of size and

geographic location—to test the model's generalizability. These research directions will help educators and administrators create more informed and inclusive frameworks for AI integration in higher education.

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