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# Factors Influencing International Students' Adoption of Generative Artificial Intelligence: The Mediating Role of Perceived Values and Attitudes

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**ABSTRACT**

*GenAI has revolutionized higher education across the globe. One group that is particularly impacted is international students. We examined the factors influencing international students' intentions to use GenAI. We recruited participants studying in the U.S. through an online survey. Our results suggest that attitudes toward GenAI use, PEU, PU, enjoyment, subjective norms, novelty, trust in technology, perceived value, and AI literacy are positively associated with the intention to use GenAI. Fear of plagiarism had a negative relationship with the intention to use GenAI. Trust in technology, PEU, fear of plagiarism, PU, and AI literacy indirectly influence GenAI usage intention via attitude and perceived value, underscoring both the appeal and concerns of GenAI in learning. This* *study contributes to theoretical frameworks on technology adoption and use by demonstrating (*i.e.*, the TPB, VAM, and TAM) how cognitive, affective, and value-based factors collectively influence the adoption of GenAI technologies and offers policy and practical implications for higher education.*

**Keywords:** GenAI, international students, perceived value, theory of planned behavior, value-based adoption model, technology acceptance model

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## INTRODUCTION

In the race to adapt to generative AI (GenAI), students are not just competing—they are competing with versions of themselves augmented by AI. Rapid advancements in GenAI have had a profound impact on higher education (Stöhr et al., 2024). Recently, the implementation of GenAI in higher education has influenced teaching and learning at all levels (Ittefaq et al., 2024; Stöhr et al., 2024). For example, AI-based tools offer personalized learning experiences for students, enhance writing quality through real-time feedback on grammar, and automate assessments for teachers (Holmes & Tuomi, 2022). While GenAI enhances education in terms of research, pedagogy, and practice, it also poses significant risks. GenAI can generate incorrect answers, produce fake data, facilitate plagiarism, lead to declines in cognitive skills, undermine academic integrity, and result in problematic assessments (Abdaljaleel et al., 2024; von Garrel & Mayer, 2023). In examining the role of GenAI in higher education, many existing studies have focused on domestic student samples within particular countries (Abbas et al., 2024; Li, 2023; Stöhr et al., 2024; von Garrel & Mayer, 2023; Wood & Moss, 2024), leaving a critical gap in understanding GenAI use among international students.

Studying the international student population is important for several key reasons. First, international students often encounter cultural differences, language barriers, psychological challenges in a new environment, and limited financial resources (Seo et al., 2023). Second, many of these students come from countries where English is not their first or national language. Upon arriving in an English-speaking country such as the U.S., they may struggle with writing, grammar, and punctuation. Third, they receive less informational support from peers and teachers, which can hinder their academic performance (Baines et al., 2022). As a result, this minority group may be more inclined to use GenAI-based tools to enhance their learning and academic performance. Finally, they often find it beneficial to use digital communication technologies, including GenAI, to complete assignments and learn new skills (Abdaljaleel et al., 2024). Prior research has indicated that perceived ease of use and perceived usefulness can increase students' motivation to use GenAI (Romero-Rodríguez et al., 2023; Sohn & Kwon, 2020).

The present study examines the use of GenAI among international students in the U.S. Our research is informed by three theoretical frameworks: the TPB, VAM, and TAM. Empirical data come from an online survey with 245 international students currently residing in and studying at U.S. higher education institutions. This study advances the TPB, VAM, and TAM by illustrating how cognitive, emotional, and value-driven factors jointly shape international students' adoption of GenAI technologies. The research also presents a new perspective from this distinct immigrant population, offering valuable insights for academic institutions and policymakers on GenAI use among international students.

## Hypotheses

The following hypotheses were proposed:

$H_1$: PEU and PU have positive effects on an individual's intention to use GenAI.

$H_2$: Attitudes toward GenAI have positive effects on an individual's intention to use GenAI.

$H_3$: PEU and PU have positive relationships with an individual's attitudes toward the use of GenAI.

$H_4$: Subjective norms have positive effects on an individual's intention to use GenAI.

$H_5$: Enjoyment has a positive effect on an individual's intention to use GenAI.

$H_6$: Novelty has a positive effect on an individual's intention to use GenAI.

$H_7$: Perceived value is positively associated with an individual's intention to use GenAI.

$H_8$: Trust in technology has a positive relationship with an individual's intention to use GenAI.

$H_9$: AI literacy is positively associated with an individual's intention to use GenAI.

$H_{10}$: Fear of plagiarism will have a negative effect on an individual's intention to use GenAI.

$H_{11}$: The indirect effects of (a) PU, (b) PEU, (c) fear of plagiarism, (d) trust in technology, and (e) AI literacy on the intention to use AI will be mediated through attitudes.

$H_{12}$: The indirect effects of (a) PU, (b) PEU, (c) fear of plagiarism, (d) trust in technology, and (e) AI literacy on the intention to use AI will be mediated through perceived value.

## LITERATURE REVIEW

### Technology Acceptance Model (TAM)

The technology acceptance model (TAM), which Fred Davis introduced in 1989, serves as a theoretical model for understanding users' acceptance of a new technology or innovation. According to the TAM, two main factors influence whether a person will use a new technology: how useful they think it is and how easy it is to use (Davis, 1989). Over time, the model has been updated to include other factors, such as social influence and enjoyment, especially for more advanced technologies such as generative AI (Venkatesh & Davis, 2000; Venkatesh & Bala, 2008; Venkatesh et al., 2003). We use the TAM in this study because it helps explain how students decide to use different types of technology, including learning tools, mobile apps, and AI systems (Li, 2023; Pan, 2020; Salloum et al., 2019; Sohn & Kwon, 2020). In our case, the application of GenAI in higher education is a relatively new phenomenon that has recently received significant scholarly and policy attention worldwide (Shahzad et al., 2024). The TAM offers a validated framework that captures the key psychological factors (perceived usefulness and ease of use) that drive student decisions about novel learning technologies such as GenAI (Nazaretsky et al., 2025).

### Theory of Planned Behavior (TPB)

The theory of planned behavior (TPB), introduced by Ajzen in 1985, explains how and why individuals transition from forming intentions to taking action. Like the technology acceptance model (TAM), the TPB builds on the earlier theory of reasoned action (Fishbein & Ajzen, 2011). It focuses on three main factors: a person's attitudes, the influence of the people around them (subjective norms), and how much control they feel they have over their actions (perceived behavioral control) (Armitage & Conner, 2001). Together, these factors shape a person's intention, which is seen as the best predictor of what they will actually do. This model has been widely used to study behavior in many areas, including health, marketing, environmental actions, and technology use (Greaves et al., 2013; Ivanov et al., 2024). For example, Wang et al. (2024) reported that Chinese students' positive attitudes toward GenAI led to a stronger intention to use it. Similarly, Zhu et al. (2025) reported that students' awareness of ethical issues and concerns about AI risk influenced their willingness to use GenAI in their studies. Ivanov et al. (2024) also reported that the key elements of the TPB help explain both students' and lecturers' intentions to use GenAI tools. In another study, Al-Qaysi et al. (2024) reported that these same TPB factors influenced how students used ChatGPT. In our research, we use the TPB to explore how international minority students form intentions around the use of GenAI tools (Mohamed Eldakar et al., 2025).

## Value-based Adoption Model (VAM)

The value-based adoption model (VAM) helps explain why people choose to use a certain technology by focusing on how they judge its overall value (Kim et al., 2017). Introduced by Kim et al. (2007), VAM looks closely at the balance between the benefits and costs of using a new technology—an important factor in shaping whether an individual decides to adopt it (Sohn & Kwon, 2020). VAM has recently been applied in areas such as mobile apps, online shopping, social media, and digital services (Kim & Han, 2010; Turel et al., 2010). For example, in their study of smart home services, Kim et al. (2017) reported that users who perceived greater benefits were more likely to view the technology as valuable, whereas concerns such as privacy risks or resistance to change diminished its perceived value. In the current study, we integrate the VAM with the TAM and TPB to provide a more comprehensive theoretical foundation for understanding why users may accept or reject innovations such as GenAI (Park et al., 2025).

## Research Model

### *Intention to Use GenAI*

Intention is a key factor driving the use of GenAI across various domains, including education (Wang et al., 2024). Research suggests several key determinants influencing users' intentions to adopt GenAI tools. For example, individuals are more gravitated toward embracing GenAI while perceiving it as a means to increase productivity or performance (Diao et al., 2024). Perceived ease of use also plays an important role in reducing barriers to adoption (Shahzad et al., 2024). Additionally, social influence, including the role of peers and online communities, significantly shapes awareness and adoption intentions (Parveen et al., 2024). Individual characteristics, such as personal innovativeness and trust in AI technologies, further influence their technology intention (Zogheib & Zogheib, 2024). In educational settings, while students generally hold favorable attitudes toward integrating GenAI in teaching and learning, concerns about academic integrity and the need for clear usage guidelines remain pressing issues (Chan & Hu, 2023). This study seeks to analyze the factors influencing international students' intentions to adopt GenAI by examining variables associated with the TAM, TPB, and VAM.

### *Perceived Ease of Use (PEU) and Perceived Usefulness (PU)*

The PEU is defined as “the degree to which a person believes that using a particular information system would enhance his/her job performance” (Davis, 1989, p. 320). In the context of emerging technologies, this concept can be applied to international students’ use of GenAI, reflecting their tendency to adopt such tools on the basis of their belief that it will improve their academic performance (Li, 2023). Similarly, PU is referred to as “the degree to which an individual believes that using a particular system is free of physical and mental effort” (Davis, 1989, p. 320). For example, tools such as ChatGPT require minimal effort to complete tasks. Research suggests that both PEU and PU notably influence users’ intentions to utilize GenAI (Li, 2023; Wang et al., 2023).

### *Attitudes toward GenAI*

Past studies highlight the importance of users’ attitudes toward technology, claiming that these attitudes are crucial in their ability to engage with new and emerging technologies (Serholt et al., 2014). For instance, a negative attitude toward technology or products is associated with adverse perceptions of Gen-AI tools and low interest in online learning. Such perceptions hinder effective technology use, thereby creating hurdles in students’ learning (Hashim et al., 2021). Kim and Lee (2024) identified several factors that shape attitudes toward GenAI, including indirect and direct experiences with AI, the sociocultural influence of gender, exposure to AI education, and familiarity with programming languages. As a result, these factors can contribute both positively and negatively to students’ attitudes toward using AI.

### *Subjective Norms*

According to Ajzen (1991), subjective norms refer to users’ perceptions of social pressure to perform or avoid a certain behavior. In particular, it reflects the belief that significant others—such as fellow students, friends, or colleagues—approve or disapprove of a behavior (Li, 2023). In the context of technology adoption, subjective norms are a key factor influencing people’s decisions. It examines the impact of societal and peer expectations on behavioral intentions (Ivanov et al., 2024). Research suggests that subjective norms influence individuals’ intentions to use AI (Li, 2023). This relationship also holds true for the adoption of other technological developments. For example, Lee (2009) suggested that “subjective norm positively influences individuals’ intention to play online games” (p. 866).

### *Enjoyment*

Enjoyment refers to the “degree to which the activity of using technology is perceived to be enjoyable in its own right, apart from any performance consequences that may be anticipated” (Teo & Noyes, 2011, p. 1646). Enjoyment means that users find interactions with GenAI pleasant and engaging. For example, engaging in a conversation with GenAI tools can be entertaining, as users receive valuable information through these interactions. Humans are inherently curious, and interacting with GenAI can be an enjoyable and fun experience. Additionally, GenAI allows users to ask questions that they might hesitate to ask other people, further enhancing its appeal. For these reasons, GenAI can be perceived as fun, enjoyable, and entertaining for users.

### *Novelty*

Novelty assesses the uniqueness of an idea, product, or service, as well as how they are perceived on the basis of their freshness and originality (Kim et al., 2017). With respect to new technologies and GenAI, novelty is embodied by new products and distinctive features that significantly enhance user experiences. When users perceive the novelty value of a technology, they are more likely to engage with it in an enjoyable manner, which consequently enhances their intention to use it (Adapa et al., 2020). Previous research has identified novelty value as a key belief regarding technological innovations, playing a crucial role in determining whether a technology is accepted or rejected (Al-Abdullatif & Alsubaie, 2024). Studies have also demonstrated the presence of a novelty effect in user interactions with GenAI (Ma & Huo, 2023). As disruptive innovations in the field of natural language processing (NLP), GenAI products leverage their novelty value to attract and sustain user attention while reducing psychological resistance to new technologies (Xie et al., 2022).

### *Perceived Value*

Perceived value is grounded in the cost–benefit approach, which represents the decision-making process in which individuals weigh the cost of uncertainty against the potential benefits of adopting a new technology, product, or service (Lin et al., 2012). In academic settings, GenAI involves evaluating the personal costs associated with their use (Gansser & Reich, 2021). For example, research indicates that individuals are more inclined to embrace a technology when they view it as both effective and cost-effective (Gansser & Reich, 2021). The present study defined perceived value as the extent to which international students in the U.S. believe that the cost associated with the use of GenAI is justified by its benefits. Many GenAI products are free to use, but advanced features often require a fee.

### *Trust in Technology*

Trust comprises psychological mechanisms that reduce uncertainty and increase the likelihood of positive interaction with entities (Lukyanenko et al., 2022). Individuals spend less cognitive and physiological energy on trusted entities, and this phenomenon is regarded as a critical aspect of GenAI usage (Lukyanenko et al., 2022). Prior studies have examined the role of trust in the intention to use AI among college students. For instance, Choung et al. (2023) reported that trust positively influences individuals' intention to use AI technologies such as voice assistants. Other studies have shown that trust is crucial for both adopting AI technologies and addressing concerns about their use (Omrani et al., 2022). Similarly, in their study contextualizing the use of AI-based solutions in organizational supply chains, Hasija and Esper (2022) suggested that trust is a critical factor for adopting AI technologies and underscored the importance of investigating technology acceptance and use through the lens of trust.

### *AI Literacy*

AI literacy is conceptualized as individuals' ability to interact with AI technologies. It is considered one of the key factors in GenAI adoption (Ng et al., 2024). Research suggests that AI literacy enhances users' ability to engage with GenAI tools, as demonstrated by studies where higher AI literacy, measured through objective tests, predicts better task performance (Jin et al., 2024). In educational contexts, higher AI literacy fosters the ability to critically evaluate GenAI outputs, increasing confidence and trust in AI tools (Huang et al., 2023; Wood & Moss, 2024). These findings suggest that the intention to use GenAI tools and AI literacy are likely to be positively associated.

### *Fear of Plagiarism*

Plagiarism means the use of "another person's work, ideas, or intellectual property without proper credit" while falsely claiming it as one's own (Giray, 2024, p.2; Kampa et al., 2025). This unethical practice can manifest in various forms, including copying text verbatim, paraphrasing without citation, or failing to acknowledge someone's ideas or research findings. A growing concern involves students using GenAI to produce essays or assignments and submitting them as their own without acknowledging the use of such tools. Giray (2024) highlighted that the fear of being accused of plagiarism negatively affects students' willingness to engage with AI. This fear is particularly pronounced among nonnative English speakers, who may worry about false positives when their work is evaluated. Khalaf (2025) examined attitudes toward plagiarism and aigiarism (AI-assisted plagiarism), revealing that these concerns discourage students from using GenAI tools. The study underscores the need to address these fears to foster a more informed and ethical use of AI in academic contexts.

### *Mediating Role of Attitude and Perceived Value*

Attitude, as a mediator in technology adoption models, has been widely studied. In the original TAM, attitude was proposed as a mediator between PU, PEU, and behavioral intention (Davis, 1989). However, TAM 2 and TAM 3 suggest that attitude's mediating effect is a weak factor, leading some researchers to exclude it from the model (Venkatesh & Davis, 2000). Nevertheless, studies continue to support the mediating role of attitudes. For example, a study on technology-based self-directed learning suggested that attitudes mediate the relationships among technology acceptance, technological self-efficacy, and learning outcomes (Pan, 2020). Other studies have found partial mediation of attitude, such as Lai (2016), who suggested that attitude partially mediated the effect of PEU on intention, accounting for 46.57% of the direct effect.

Trust in technology is an important factor in shaping perceived value. Ahmetoglu et al. (2023) reported that digital trust positively influences perceived value in the usage of new technologies. Zhao and Chen (2021) reported that higher perceived value strongly influences purchase intentions for environmentally friendly homes in China. Similarly, Hsu and Lin (2016) reported that perceived value significantly affects users' intention to adopt Internet of Things (IoT) services. Other studies have identified perceived value as another key factor driving the intention of behavioral adoption (Davis, 1989; Prasad & De, 2024). User perceptions of the perceived value associated with GenAI tools in organizational contexts positively influence adoption decisions (Prasad & De, 2024). Moreover, technology adoption models consistently emphasize that perceived value acts as a mediator in the relationship between knowledge and the intention to use technology (Davis, 1989; Venkatesh et al., 2003). Factors such as AI literacy and fear of plagiarism also contribute to shaping perceived value. Al-Abdullatif and Alsubaie (2024) reported that the perceived value of ChatGPT among students strongly influences their intention to use it. Their findings further revealed that PU, perceived fees, and perceived enjoyment largely influenced the perceived value of ChatGPT, whereas perceived risk had no effect on Saudi students.

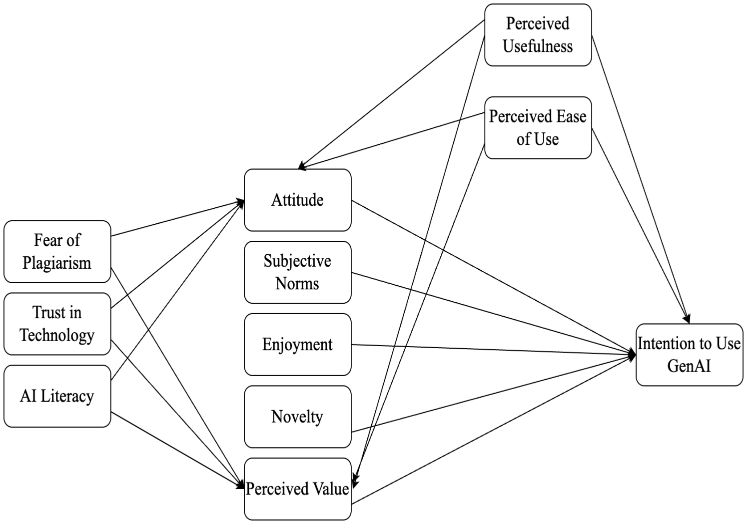


**Figure 1: Research Model**

## METHOD

### Participant Demographics

A sample of 245 participants was recruited from on-campus student organizations at various universities across the U.S. Eligible participants had to (a) self-identify as international students, (b) be 18 years of age or older and currently reside and study in the U.S. The average age of the participants was 28.14 years (SD = 8.25). A greater proportion of men (59.2%) than women (38.8%) participated in the study, with 2% of the participants choosing other gender categories. The participants also represented diverse racial groups (e.g., 20 unique races, including Hispanics, East Asians, South Asians, and Africans), home countries (e.g., 54 unique countries) and mother tongues (e.g., 42 different languages). Furthermore, 63.3% of the participants were enrolled in an undergraduate program at U.S. universities, followed by 33.1% in a graduate/Ph.D./postdoc program, 0.4% in a language program, and 3.3% in other programs. All the measurement items discussed below were on a five-point Likert scale (1: strongly disagree to 5: strongly agree).

### Measurements

Appendix A presents the measurement items for each variable, which are informed by previous studies as described below.

#### *Intention to Use GenAI*

The measurement items related to the intention to use GenAI were modified from research by Ajzen (1991) and Ivanov et al. (2024). A higher score indicates a greater intention to use GenAI. The index variable was reliable (Cronbach's $\alpha = .78$), and the survey sample demonstrated a high level of intention to use GenAI ($M= 3.76$, $SD= .79$).

#### *Perceived Usefulness (PU)*

The PU was measured with four items from the works of Davis (1989) and Li (2023). A higher score indicates a greater level of perceived usefulness of AI. The index variable was reliable (Cronbach's $\alpha = .86$), and the survey sample indicated a high level of perceived usefulness of AI ($M= 3.98$, $SD= .85$).

#### *Perceived Ease of Use (PEU)*

PEU was measured with four items from Davis (1989) and Li (2023). A higher score indicated that participants perceived a greater level of ease of AI use. The index variable was reliable (Cronbach's $\alpha = .81$), and the survey sample demonstrated a high level of ease of use related to GenAI ($M= 4.06$, $SD= .71$).

### *Attitudes toward GenAI*

Attitude toward the use of GenAI was measured with four items (Ajzen, 1991; Ivanov et al., 2024; Li, 2023). A higher score indicated that the participants had a more positive attitude toward using AI. The index variable was reliable (Cronbach's $\alpha$ = .89), and the survey sample showed a positive attitude toward using GenAI (*M* = 3.79, *SD* = .97).

### *Subjective Norms*

Subjective norms were measured with four items (Ajzen, 1991; Ivanov et al., 2024; Li, 2023). A higher score indicated that participants perceived a greater level of social expectation to use AI. The index variable was reliable (Cronbach's $\alpha$ = .83), and the survey sample demonstrated a high likelihood of using GenAI to meet social expectations (*M*= 3.64, *SD*= .87).

### *Enjoyment*

Enjoyment was measured with three items from Agarwal and Karahanna (2000). These items have been widely used in other studies (Huang et al., 2024). A higher score indicates a greater level of enjoyment using AI. The index variable was reliable (Cronbach's $\alpha$ = .90), and the survey sample showed a high level of enjoyment when GenAI was used (*M*= 3.87, *SD*= .94).

### *Novelty*

Novelty was measured with three items from the study of Wells et al. (2010). A higher score indicates a greater level of novel experience from using AI. The index variable was reliable (Cronbach's $\alpha$ = .84), and the survey sample demonstrated a high level of novel experience from using GenAI (*M*= 3.87, *SD*= .86).

### *Perceived Value*

Perceived value was measured with five items from Kim et al. (2007). A higher score indicates a higher level of perceived value of using AI. The scale was reliable (Cronbach's $\alpha$ = .87), and the survey sample showed a high level of perceived value of using AI (*M*= 3.90, *SD*= .83).

### *Trust in Technology*

Trust in technology was measured with seven items based on previous studies (Koufaris & Hampton-Sosa, 2004; McKnight et al., 2002). A higher score represents a higher level of trust in technology. The index variable was reliable (Cronbach's $\alpha$ = .89), and the survey sample showed a high level of trust in technology (*M*= 3.71, *SD*= .79).

### *AI Literacy*

AI literacy was measured with five items reported by Wang et al. (2023). A higher score indicates a higher level of literacy related to AI. The index variable was reliable (Cronbach's $\alpha$ = 78), and the survey sample reported a high level of literacy related to GenAI (*M*= 3.96, *SD*= .70).

### *Fear of Plagiarism*

Fear of plagiarism was measured with five items from several studies published in higher education journals (Jarrah et al., 2023; Jereb et al., 2018; Khalaf, 2025; Kier & Ives, 2022). The index variable was reliable (Cronbach's $\alpha$ = 78), and the survey sample demonstrated a slightly high level of fear of plagiarism with respect to GenAI use (*M*= 3.47, *SD*= .99).

## Statistical Analysis Approach

To test hypotheses H1 through H10, we conducted a hierarchical linear regression analysis via SPSS version 28.0 with GenAI as the dependent variable. In this model, we entered the independent variables in ten sequential steps: perceived usefulness (PU), perceived ease of use (PEU), subjective norms, attitudes, enjoyment, novelty, perceived value, trust in technology, AI literacy, and fear of plagiarism. Each variable was added step-by-step to examine its unique contribution to the model and to observe how the explained variance in the dependent variable changed across steps. This approach allowed us to assess the incremental predictive power of each factor in shaping users' intention to use GenAI.

To test H11 and H12, we conducted mediation analyses via Hayes' PROCESS macro (Model 4) in SPSS version 28.0. PROCESS Model 4 is used for simple mediation analysis. This approach allowed us to test whether the relationship between the independent and dependent variables was mediated through a proposed mediator one by one. We used a bootstrapping procedure with 5,000 resamples to generate bias-corrected confidence intervals, which provides a more reliable estimation of indirect effects without assuming a normal distribution.

# RESULTS

Through an online survey of international students residing in and studying in the U.S., this study examines which factors influence their intention to use GenAI. The results of our hypothesis testing are presented below.

For hypotheses H1-H10, we first tested a hierarchical linear regression model by entering the intention to use GenAI as the dependent variable and PU, PEU, subjective norms, attitudes, enjoyment, novelty, perceived value, trust in technology, AI literacy, and fear of plagiarism as independent variables at steps

1-10, respectively. All the independent variables jointly predicted 63% of the variance in the intention to use GenAI [($F(10, 234) = 39.8$, $p < .001$)]. Then, we performed linear regression analysis of each independent variable separately while entering the intention to use GenAI as the dependent variable. Overall, these regression models indicated that the R-square values for the independent variables varied from .02-.50. Table 1 summarizes these analysis results.

**Table 1: Linear regression models for each independent variable where the intention to use GenAI was the dependent variable**

| Independent Variables | F (p) | R-square |
|---|---|---|
| Perceived usefulness | 162.8 (<.001) | .40 |
| Perceived ease of use | 46.6 (<.001) | .16 |
| Attitude | 224.9 (<.001) | .48 |
| Subjective norms | 114.5 (<.001) | .32 |
| Enjoyment | 157.3 (<.001) | .39 |
| Novelty | 117.4 (<.001) | .33 |
| Perceived value | 240.2 (<.001) | .50 |
| Trust in technology | 245.2 (<.001) | .50 |
| AI literacy | 107.5 (<.001) | .31 |
| Fear of plagiarism | 5.8 (<.05) | .02 |

*Note:* Hypothesis df: 1; df = 243

In particular, PU had a statistically significant positive effect ($\beta = .63$, $t(243) = 12.8$, $p < .001$), and PEU ($\beta = .40$, $t(243) = 6.8$, $p < .001$), attitude ($\beta = .69$, $t(243) = 14.9$, $p < .001$), subjective norms ($\beta = .57$, $t(243) = 18.7$, $p < .001$), enjoyment ($\beta = .63$, $t(243) = 12.5$, $p < .001$), novelty ($\beta = .57$, $t(243) = 10.8$, $p < .001$), perceived value ($\beta = .71$, $t(243) = 15.5$, $p < .001$), trust in technology ($\beta = .71$, $t(243) = 15.6$, $p < .001$), and AI literacy ($\beta = .55$, $t(243) = 10.4$, $p < .001$) had positive effects on the intention to use GenAI. In contrast, fear of plagiarism had a negative effect ($\beta = -.15$, $t(243) = -2.4$, $p < .05$) on the intention to use GenAI. Therefore, H1a, H1b, H2, H4, H5, H6, H7, H8, H9, and H10 were supported. Table 2 presents these analysis results.

**Table 2: Independent variables in linear regression models where the intention to use GenAI was entered as the dependent variable**

| Independent Variables | Standardized Beta | *t* | *p* |
|---|---|---|---|
| Perceived usefulness | .63 | 12.8 | <.001 |
| Perceived ease of use | .40 | 6.8 | <.001 |
| Attitude | .69 | 14.9 | <.001 |
| Subjective norms | .57 | 10.7 | <.001 |
| Enjoyment | .63 | 12.5 | <.001 |
| Novelty | .57 | 10.8 | <.001 |
| Perceived value | .71 | 15.5 | <.001 |
| Trust in technology | .71 | 15.6 | <.001 |
| AI literacy | .55 | 10.4 | <.001 |
| Fear of plagiarism | -.15 | -2.4 | <.05 |

To test Hypothesis H3, we performed hierarchical linear regression analysis by entering attitude as the dependent variable and perceived usefulness as the independent variable at step 1 and perceived ease of use at step 2. The regression models revealed that both independent variables jointly predicted 42% of the variance in attitude [$F(2, 242) = 87.5$, $p < .001$], whereas PU separately estimated 41% of the variance in attitude [$F(1, 243) = 169.2$, $p < .001$], and PEU estimated 1% of the variance in attitude [$F(1, 242) = 3.9$, $p = .05$]. Specifically, PU had a positive and statistically significant effect on attitude ($\beta = .58$, $t(243) = 9.3$, $p < .001$), whereas more specifically, PEU had a positive but statistically insignificant effect on attitude ($\beta = .12$, $t(243) = 1.2$, $p = .05$). Thus, H3a was supported, whereas H3b was not.

To test H11 and H12, we conducted mediation analyses via PROCESS Model 4 at bootstrapping with 5,000 samples. Our results suggested that PU (i.e., PU → attitude → intention to use GenAI) had a positive and significant indirect effect (*Effect* = .29, *SE* = .05, 95% CI [.18, .38]), whereas PEU (i.e., PEU → attitude → intention to use GenAI) also had a positive and significant indirect effect (*Effect* = .31, *SE* = .06, 95% CI [.20, .43]) on the intention to use GenAI. Similarly, fear of plagiarism (i.e., fear of plagiarism → attitude → intention to use GenAI) had a negative and significant indirect effect (*Effect* = -.18, *SE* = .04, 95% CI [-.26, -

.16]), trust in technology (i.e., trust in technology → attitude → intention to use GenAI) had a positive and significant indirect effect (*Effect* = .27, *SE* = .07, 95% CI [.14, .41]), and AI literacy (i.e., AI literacy → attitude → intention to use GenAI) had a positive and significant indirect effect (*Effect* = .32, *SE* = .06, 95% CI [.21, .43] on the intention to use GenAI. Thus, H11a, H11b, H11c, H11d, and H11e were supported. Figure 2 provides a visual description of the indirect effects of PU, PEU, fear of plagiarism, trust in technology, and AI literacy on the intention to use GenAI mediated through attitudes.

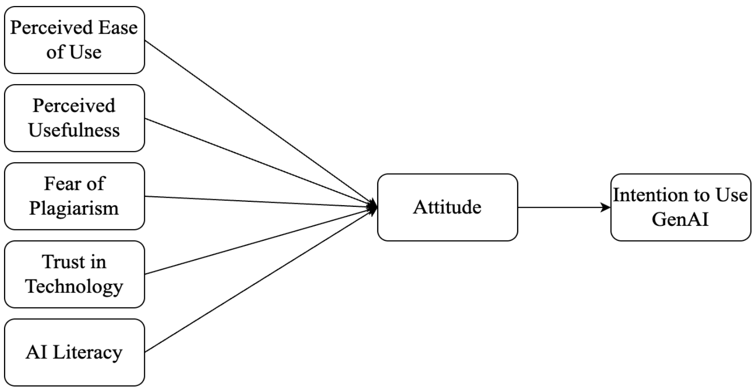


**Figure 2: Indirect effects of PU, PEU, fear of plagiarism, trust in technology, and AI literacy on the intention to use GenAI mediated through attitude (H11)**

Likewise, PU (i.e., PU → perceived value → intention to use GenAI) had a positive and significant indirect effect (Effect = .32, SE = .05, 95% CI [.22, .41]), and PEU (i.e., PEU → perceived value → intention to use GenAI) had a positive and significant indirect effect (Effect = .37, SE = .07, 95% CI [.24, .51]) on the intention to use GenAI. Similarly, fear of plagiarism (i.e., fear of plagiarism → perceived value → intention to use GenAI) had a negative and significant indirect effect (Effect = -.11, SE = .04, 95% CI [-.19, -.03]), trust in technology (i.e., trust in technology → perceived value → intention to use GenAI) had a positive and significant indirect effect (Effect = .30, SE = .05, 95% CI [.19, .40]), and AI literacy (i.e., AI literacy → perceived value → intention to use GenAI) had a positive and significant indirect effect (Effect = .38, SE = .06, 95% CI [.27, .50]) on the intention to use GenAI. Hence, H12a, H12b, H12c, H12d, and H12e were also supported. Figure 3 provides a visual description of the indirect effects of PU, PEU, fear of plagiarism, trust in technology, and AI literacy on the intention to use GenAI mediated through perceived value.

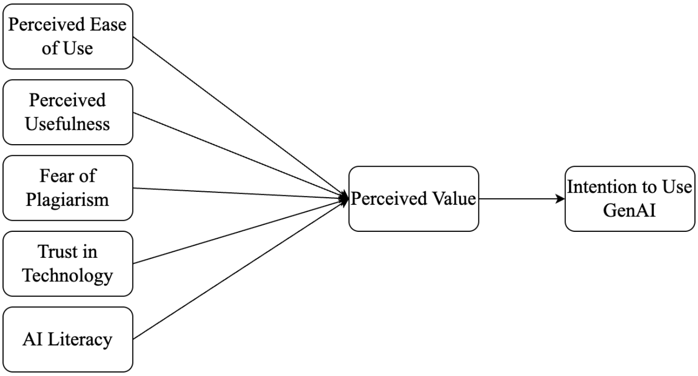


**Figure 3: Indirect effects of PU, PEU, fear of plagiarism, trust in technology, and AI literacy on the intention to use GenAI mediated through perceived value (H12)**

## DISCUSSION

Amid the rapid advancements in GenAI technologies in recent years, universities across the world have grappled with identifying effective strategies to integrate GenAI into teaching, research, and other facets of higher education (Stöhr et al., 2024). This study analyzed what factors influence intentions to adopt GenAI tools such as ChatGPT among international students at U.S. universities, a population that has been understudied in this area of research. The findings from our survey research have important scholarly and practical implications.

### Scholarly Implications

Our research showed that PU and PEU have positive effects on both attitudes toward GenAI and intentions to use it. That is, international students who perceive GenAI tools to be useful and easy to use are more likely to utilize GenAI. This finding aligns with prior empirical research (Li, 2023; Wang et al., 2023) as well as the TAM, which highlights the important roles of PU and PEU in adopting new technologies (Davis, 1989; Venkatesh & Davis, 2000). Similarly, our study revealed that attitudes toward GenAI were positively associated with GenAI use intention. Those who view AI as beneficial are more inclined to use GenAI. These results are consistent with the findings of Serholt et al. (2014) and Kim and Lee (2024), who highlight the important role of individual attitudes in facilitating technology adoption. According to our survey research, not only participants' own attitudes toward GenAI but also their perceptions of how others think of GenAI influence their GenAI use intention. Subjective norms, an individual's perception of social expectations or pressure from other people, as measured by four items in this study, had a significant positive relationship with GenAI use intention. This result aligns with the TPB and the findings of Li (2023), which highlight the significant impact of peer and social influences on shaping adoption behavior.

This study contributes to advancing theoretical frameworks such as the TPB, the TAM, and the VAM. First, it extends these frameworks by incorporating enjoyment and novelty within the context of GenAI. Second, it highlights the importance of other factors, such as trust in technology, AI literacy, and fear of plagiarism, in examining users' intention to use GenAI. Third, the findings confirm that enjoyment and novelty are significant drivers of the intention to use GenAI. This is similar to the work of Adapa et al. (2020) and Ma and Huo (2023), who identified these factors as key contributors to user engagement with emerging technologies. By integrating new variables into existing frameworks, this study provides more fresh insights into these models. In contrast, we found that fear of plagiarism negatively influenced the intention to use GenAI, suggesting that concerns about plagiarism act as a deterrent to adopting GenAI. When international students fear that using GenAI might lead to unintentional plagiarism or ethical issues, they are less likely to embrace the technology. This finding aligns with those of previous studies (Giray, 2024; Khalaf, 2025) that identified plagiarism concerns as a significant barrier to adoption, particularly in educational settings. These challenges, including issues such as AI-generated plagiarism ("Aigiarism") and difficulties in assessment, are especially pronounced among nonnative and international students (Khalaf, 2025).

Our results also underscore the importance of trust in technology and AI literacy in shaping user intentions, which is consistent with the findings of Lukyanenko et al. (2022) and Huang et al. (2023), who identified trust and individuals' familiarity and competence with AI tools as key predictors of effective GenAI adoption. Additionally, perceived value emerged as a significant factor in adoption decisions, supporting the cost–benefit paradigm in technology adoption emphasized by Gansser and Reich (2021). The mediating roles of attitude and perceived value in connecting key predictors—such as PU, PEU, trust, and AI literacy—to user intentions are in line with the integrated perspectives of the TAM, TPB, and VAM. These findings highlight the interplay of cognitive, affective, and value-based factors in shaping behavioral intentions.

## Practical and Policy Implications

A transformative academic equalizer, GenAI, offers international students real-time writing aid, individualized learning support, and fast access to knowledge previously limited by language hurdles. However, its increasing proliferation has also disrupted traditional assessments of authentic learning, requiring new frameworks to evaluate critical thinking in an AI-augmented world. Such impediments raise important questions about the need for clear, consistent guidelines, including ethical practices surrounding the use of GenAI in academic institutions.

Institutions need to balance GenAI's democratizing potential with protection against overreliance and threats to academic integrity to define educational equity in the digital age (Malik et al., 2025). Our findings suggest that while international students recognize specific benefits of using GenAI, such as information gathering, they remain uncertain about how to navigate varying instructors' expectations for its use in assignments. In particular, the fear of plagiarism may prevent international students from fully harnessing the benefits of GenAI. We offer four major recommendations as follows:

### *Creation of GenAI Task Forces*

From a policy perspective, these findings can inform university authorities and task forces involved in developing AI-related policies for higher education. We advocate for the formation of distinct working groups dedicated to GenAI. Task forces should implement flexible, always developing frameworks—such as routinely revised rules and inclusive policy feedback mechanisms—to align with improvements in GenAI while fostering ethical usage. For example, universities should prioritize launching training sessions and workshops specifically designed for domestic and international students to help them understand the appropriate uses and potential pitfalls of GenAI in academic settings (Malik et al., 2025).

### *Develop effective and transparent GenAI guidelines*

It would be helpful for each discipline or institution to develop consistent guidelines on when the use of GenAI is appropriate and when it is not to reduce student confusion and concern. The rules and guidelines should specify approved applications (e.g., brainstorming, coding assistance), restricted uses (e.g., replacing core assessments), and disclosure requirements. For example, an engineering school might allow AI for debugging but not for final design submissions, whereas a literature course might allow AI-assisted analytical drafts but needs unique critical essays. This transparency ensures that students use AI responsibly without sacrificing skill development while preserving uniformity across courses. We also argue that faculty–student collaboration in developing these norms will encourage realistic, transparent implementation.

### *Training Workshops*

As GenAI tools continue to evolve, it is important for both instructors and students to participate in regular workshops to collaboratively develop practical guidelines for the ethical use of GenAI. Curriculum designers must emphasize GenAI's perceived usefulness and ease of use through hands-on workshops that are relevant to discipline demands while simultaneously introducing controls to reduce academic integrity risk. Similarly, professional development seminars for educators are essential to deepen their understanding of international students' motives and challenges in using AI technologies. To strengthen trust in emerging technologies, institutional policies should leverage subjective norms by involving faculty members as role models for the ethical application of GenAI. Furthermore, all stakeholders, including technology companies and higher education institutions, must work together to build trust, enhance AI literacy among students, and establish clear guidelines.

### *Recognition of Potential Biases in GenAI*

Student and teacher training should instill the recognition that GenAI technologies may contain societal biases embedded in their training data, such as cultural preconceptions, racial assumptions, or language limitations. By critically analyzing outputs for these biases, learners might avoid promoting damaging narratives while using AI's potential more ethically. For example, a history student utilizing ChatGPT should double-check information for Western-centric perspectives. In a similar vein, brief training courses or assignment reflections can increase awareness, transforming GenAI from a passive tool to a catalyst for informed digital literacy.

## CONCLUSION

Our study offers useful insights for future scholarships in the areas of GenAI, higher education, and technology in society. By integrating the TAM, TPB, and VAM, this research addresses a critical gap in understanding how different factors emphasized in each framework—such as perceived usefulness, social norms, trust, and value perception—collectively influence international students' adoption of GenAI. In particular, by focusing on this underserved demographic, our study provides a foundation for developing more inclusive theoretical and practical approaches. Such approaches can assist international students in leveraging the benefits of GenAI while maintaining academic integrity (Strzelecki, 2024). Insights from our research can also help educators and policymakers develop tailored strategies to address the particular needs and concerns of international students, ultimately promoting equitable access and effective integration of GenAI tools in academic settings. These dynamic approaches must reconcile innovation with accountability, guaranteeing that GenAI augments learning without undermining academic integrity. By ensuring equitable access to guidance and support, educational institutions can enable all students, especially those from diverse or international backgrounds, to utilize GenAI ethically and efficiently, transforming it into a tool for inclusion and academic growth rather than a source of disparity.

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- [x] *None*
- [ ] *Some sections, with minimal or no editing*
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- [ ] *Entire work, with minimal or no editing*
- [ ] *Entire work, with extensive editing*

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## APPENDIX A: MEASUREMENT ITEMS

**Intention to Use GenAI**
(1) For creative writing (i.e., essays, assignments, letters, and emails)
(2) Linguistic assistance (i.e., translations, improving English, grammar, editing)
(3) Generating ideas (i.e., pitches, homework, class ideas, class discussion, presentations)
(4) Assisting in solving problems (i.e., computer programming, mathematical problems, statistical issues, coding, python, R)
(5) Preparing job-related materials (i.e., resume/CV, cover letters, DEI statements, research statements, teaching statements)
(6) Seeking information about key issues (history, politics, climate, healthcare)

**Perceived Usefulness (PU)**
(1) Enabling me to accomplish tasks more quickly
(2) Improving my performance
(3) Increase my productivity
(4) Enhance my effectiveness

**Perceived Ease of Use (PEU)**
(1) Learning to use AI would be easy for me
(2) I would find it easy to get AI to do what I want to do
(3) I would find AI clear and understandable
(4) It would be easy for me to become skillful at using AI

**Attitudes toward GenAI**
(1) I think using AI is a good idea
(2) I believe it would be beneficial for me to use AI
(3) I consider that people should use AI
(4) I think using AI is a better choice

**Subjective Norms**
(1) Many people like me think that using AI is a good idea
(2) Many people in my circle use AI
(3) The people whom I turn to for advice expect me to use AI
(4) Many of my friends think that it is better to use AI

**Enjoyment**
(1) I have fun interactions with AI (such as ChatGPT)
(2) Using AI provides me with a lot of enjoyment
(3) I enjoy using AI

**Novelty**
(1) I found using AI to be a novel experience
(2) Using AI (such as ChatGPT) is new and refreshing
(3) AI represents a neat and novel way of doing things

**Perceived Value**
(1) Compared with the time I need to spend, the use of AI is worthwhile for me
(2) Compared with the effort I need to put in, the use of AI is beneficial for me
(3) The use of AI delivers good value for me
(4) Using AI saves me time and effort when performing tasks
(5) the fee that I have to pay for the use of AI is reasonable

**Trust in Technology**
(1) Trustworthy
(2) Well reputed
(3) Competency
(4) Efficiency
(5) Reliability
(6) Consistency
(7) Flexibility

**AI Literacy**
(1) I can skillfully use AI tools to help me with my daily work
(2) I can evaluate the capabilities and limitations of an AI tool after it is used.
(3) I can choose the most appropriate AI tool from a variety of options for a particular task.
(4) I can choose a proper solution from various solutions provided by AI tools
(5) I am aware of privacy and information security issues when using AI applications

**Fear of Plagiarism**
(1) I am not confident in my ability to avoid plagiarism when using AI tools for research or writing.
(2) I am worried about unintentionally plagiarism when using AI tools to assist with my assignments.
(3) I believe that using AI tools increases the risk of being accused of plagiarism.
(4) I feel anxious about properly citing sources when using AI tools for academic tasks
(5) I think that AI tools make it easier for students to plagiarize without realizing it.