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Modeling user perceptions of generative artificial intelligence in education through technology acceptance theory and a trust-risk framework

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Abstract

Generative Artificial Intelligence (AI), including Large Language Models (LLMs), is a technological revolution that has yet unknown impacts on our society. This study applies the Technology Acceptance Model (TAM), the Trust-Risk framework, and user disposition - as measured by Experience, Self-Efficacy, and AI Orientation – to explore GenAI adoption intentions in education. The purpose of the study is to assess whether relationships identified in classic technology acceptance studies extend to GenAI in education while identifying the most significant determinants of adoption. A survey of 41 Information Technology students grounds this exploratory study in higher education, creating opportunities for future research across comparable populations. Key findings from this exploratory study include TAM variables Perceived Usefulness and Attitude Toward Use are significant predictors of Behavioral Intention, while Perceived Ease of Use has only an indirect effect via Perceived Usefulness—consistent with high user experience and seminal TAM findings ($R^2 = 0.785$ vs. 0.74 in Davis, 1989). Although later TAM versions often omitted ATU, it remains significant here and in recent e-learning studies. Trust significantly influences Attitude Toward Use, Self-Efficacy affects core TAM variables though not Trust and Risk, and AI Orientation shows no effect in this digital-native Information Technology student sample.

Keywords: Generative Artificial Intelligence, TAM, Attitude toward Use, Trust, Behavioral Intent, education

Introduction

Generative Artificial Intelligence (GenAI), Information Technology (IT), and Cybersecurity are rapidly and dynamically changing due to emerging trends and growth in digital crimes fueled by GenAI. Rapid changes in IT, particularly in Cybersecurity, require a continuously updated toolset, making training potentially difficult to maintain. GenAI offers a potential solution as a real-time tutor (Kallonas et al., 2024). The field of IT and Cybersecurity needs well-trained practitioners to effectively engage with these technologies and respond to these threats. Students need applied experience for workforce preparedness, while businesses adopting this tool require an understanding of what drives acceptance (Davis et al., 1989; Venkatesh & Davis, 2000).

While the use of AI in education is not new, the LLMs available in Generative AI and the vast training sets available on the internet are (Al-Abri, 2025; Kallonas et al., 2024; Schiff, 2021). As Generative AI becomes

more embedded in business, education, and society, the consideration of how to leverage it as an educational tool and how it will be accepted by learners surfaces as a critical topic. Studies that leverage LLMs for applied learning in Cybersecurity show promise (Ghimire et al., 2024; Kallonas et al., 2024; Sukirman et al., 2024). Our exploratory study is guided by research questions that examine the Technology Acceptance Model (TAM), the Trust-Risk framework, and user disposition - as measured by Experience, Self-Efficacy, and AI Orientation – to explore GenAI adoption intentions in education. We assess whether relationships identified in previous technology acceptance studies extend to this domain and consider the most significant determinants of GenAI in education technology acceptance. We also examine if AI Orientation affects Behavioral Intent. This study will add to the existing body of knowledge in AI education and technology adoption.

Literature review

Educational and technology adoption theories are the central focus of the literature for this paper, along with research on AI use in education and cybersecurity training. There is tension between leveraging the ‘learner-AI prompt’ in distance education and concerns that reliance on AI is undermining critical thinking or worse, being used to cheat through a degree (Kallonas et al., 2024; Melisa et al., 2025). Other ethical and social concerns are the removal of the human element, bias in the machine, and known hallucinations, or errors (Bukar et al., 2024; Munaye et al., 2025).

Despite these concerns, there are educational theories, such as Constructivism and Multimedia Learning that potentially connect to the application of GenAI in education. Constructivism is an education theory, rooted in psychology, that identifies individual experience as the method through which people learn, and one of its goals is to teach students how to learn (Bada & Olusegun, 2015). Mayer’s (2024) Cognitive Theory of Multimedia Learning is the idea that people create a mental representation of words and images that they see, which enhances learning, and that activities in this process like selecting, organizing, and integrating new information with existing knowledge complete the learning process. Kallonas et al. (2024) sees Gen AI as a potential tool in the learning process, specifically, in cybersecurity education where there may be a gap or delay in training resources due to rapidly evolving technology. GenAI is a technology based, educational resource for cybersecurity practitioners to create personalized learning plans (Kallonas et al., 2024). This approach also relates to constructivism where learners take ownership of their own learning (Bada & Olusegun, 2015). Educational theories coupled with technology adoption theories are at the center of our analysis of GenAI as a tutor.

GenAI, as a tutor, in education and Information Technology training has the potential to offer real-time, on-demand access to content that supports learning, although challenges exist. To study perceptions about LLMs and GenAI as a tutor at the intersection of education and business need for training, the Technology Acceptance Model (TAM), Trust-Risk Framework, and user disposition variables are considered. In the 1980s, Davis (1989) famously developed and studied TAM extending Theory of Reasoned Action (TRA) to better understand technology adoption. Davis et al. (1989) clarifies that the purpose of TAM is to identify external factors that impact attitudes about technology adoption. Original TAM theorizes that a person’s Behavioral Intent (BI) to use technology is influenced by Perceived Usefulness (PU) and Perceived Ease of Use (PEoU): $PU + PEoU \rightarrow BI$ (Davis, 1989). Davis (1989), Venkatesh (2000) and Venkatesh and Davis (2000) confirmed PEoU as significant in user adoption, but as a direct determinant of PU: $PEoU \rightarrow PU \rightarrow BI$. Davis et al. (1989) also evaluated ATU’s impact on Behavioral Intent: $PEoU \rightarrow PU \rightarrow ATU \rightarrow BI$. They also removed Attitude toward Use (ATU) from the model in TAM2 and focused on other variables that might influence PU, including PEoU and Experience (Venkatesh and Davis, 2000). TAM3 extended TAM2 with its focus on Experience as a moderator between Perceived Ease of Use and other variables

including Perceived Usefulness and Behavioral Intent, and they also considered Self-efficacy as a determinant of PEOU (Venkatesh and Bala, 2008).

Other studies support ATU as significant in the adoption model (Dwivedi et al., 2019; Fussell and Truong, 2022; Rondan-Cataluña et al., 2015; Venkatesh & Davis, 2000; Venkatesh et al., 2003). Although the conceptual framework from an early Davis (1986) paper incorporates system features and capabilities, original TAM predictions demonstrate some consistency across various technologies (Venkatesh, 2000; Venkatesh & Bala, 2008). This is relevant considering the pace of technological advancement and change.

In contrast, Self-Efficacy (SE) is found to be domain or task specific (Davis, 1992; Lee and Mendlinger, 2011; Marakas et al., 2007), and Bandura (1982), Davis (1989), and Davis et al. (1989) observe SE as a proximal determinant of behavior, and a mechanism by which PEOU influences ATU and BI. Abdullah and Ward (2016) observed that SE influenced PEOU with a significant, positive correlation. Considering SE is a factor in managing new technologies as studied by Bandura (1977) and Compeau and Higgins (1995), understanding SE on Gen AI adoption may be important.

Trust may also be relevant as we consider bias, hallucinations, limited transparency, and the absence of human oversight (Bukar et al., 2024; Choung et al., 2023; Kallonas et al., 2024; Munaye et al., 2025). Choung et al. (2023), based on Gillath et al. (2021), identifies that it is essential to build trust for the successful adoption and use of AI systems. Pavlou (2003) studied Trust and Risk with TAM in online transactions, based on Mayer et al.'s (1995) Integrative Model of Organizational Trust, and found that Trust is a significant predictor of intent to transact. Choung et al. (2023) found significance in Trust of AI technologies by students using an AI voice assistant. Trust and TAM variables ATU, PU, and PEOU were significant in the model and were found to directly or indirectly influence BI. This is built on Gefen et al. (2003), which identified that even if technology is easy to use and perceived as useful, people may not use it, if they don't trust it. This construct of Trust is identified as important in AI technology adoption.

Based on Al-Abri's (2025) study over a 15-week period, students had an overall positive reception to GenAI as a tutor in an online setting, citing its quick responsiveness and ability to expand topic knowledge. Kallonas et al. (2024) focused on the concept of leveraging Gen AI in a workplace to accelerate learning in the rapidly changing field of Cybersecurity with promising results specific to personalized knowledge (Munaye et al., 2025). While these studies may show promise, there are ethical and human-social concerns, along with known issues with data bias and quality that must be addressed highlighting that quality education in distance learning requires a human instructor-mediator (Schiff, 2021).

Research Methodology

The study surveyed 41 Information Technology undergraduate university students across multiple online sections about their perceptions of Generative AI as a tutor and in education based on a 7-point Likert scale with 1 as strongly agree and 7 as strongly disagree. Risk Beliefs Question 5 is reverse coded and the responses were flipped prior to data analysis. Commonly known GenAI models were referenced as examples. The survey asked questions based on TAM, the Trust-Risk framework, and user disposition questions about Artificial Intelligence Orientation, Experience, and Self-Efficacy. Students were offered extra credit to complete the survey and were, also, offered an alternative extra credit option. .

Data Analysis

Tools used for the project include Qualtrics, for the survey, and other statistical analysis tools like Excel, SPSS, and SmartPLS. Statistical methods include descriptive statistics, t-tests, correlation, and regression,

and SEM-PLS. Descriptive Statistics: include measures of Central Tendency such as the mean, median, and mode; measures of Variability such as range, variance, and standard deviation; and distribution shapes like skew and kurtosis. The t-test determines if the mean of two groups have a statistically significant difference. The independent samples t-test for comparing two unrelated groups is defined as follows (Kranzler, 2003):

$$t_{obt} = \frac{\bar{X}_1 - \bar{X}_2}{\sqrt{\left[\frac{(n_1 - 1)S_1^2 + (n_2 - 1)S_2^2}{n_1 + n_2 - 2} \right] \left(\frac{1}{n_1} + \frac{1}{n_2} \right)}}$$

Pearson's correlation measures the relationship between variables, but does not imply causation, and is expressed as follows, based on Llaudet & Imai (2023):

$$cor(X, Y) = \frac{\sum_{i=1}^n Z_i^x \times Z_i^y}{n}$$

Multiple linear regression “characterizes the relationship between the explanatory (input) variable and the response (output) variable” (Sharda et al., 2021):

$$y = B_0 + B_1x_1 + B_2x_2 + B_3x_3 + \dots + B_nx_n$$

Research Questions

Research questions that focus our analysis include questions about the effect of the Technology Acceptance Model (TAM), the trust-risk framework, and user disposition - as measured by Experience, Self-Efficacy, and AI Orientation – to explore GenAI adoption intentions in Information Technology (IT) education.

RQ1: How does GenAI Orientation influence PU, PEOU, ATU, BI, Trust, and Risk? (adapted from Ng et al., 2009 which expects high security orientation to negatively influence trust and increase risk perception, indirectly lowering PU, ATU, and BI).

RQ2: How does Self-Efficacy for GenAI in education impact PU, PEOU, ATU, BI, T, and Risk? (adapted from Bandura (1977) and Compeau & Higgins (1995) and extended as a determinant of PEOU by Venkatesh (2000) and Venkatesh & Bala, (2008)).

- H1: Self-Efficacy will positively influence PEOU (based on Venkatesh (2000) and Venkatesh & Bala (2008)).

RQ3: How does Experience (E) with GenAI in education impact PU, PEOU, ATU, BI, T, and Risk? (based on Venkatesh & Bala, 2008 which observes experience as a moderating variable)

RQ4: Which TAM variables (PU, PEOU, and ATU) impact Behavioral Intent (BI) to use GenAI in education? (based on Davis (1989), Davis et al. (1989), and Venkatesh et al. (2000))

- H2: ATU will positively influence BI (based on Davis's (1989) original TAM and more modern e-learning literature referenced in the paper).
- H3: PU will positively influence BI (based on Davis's (1989) original TAM and more modern e-learning literature referenced in the paper).
- H4: PEOU will positively influence PU, but will not directly influence BI (based on Venkatesh & Davis (2000) and Venkatesh & Bala (2008)).

RQ5: What are the primary predictors of Behavioral Intent (BI) to use GenAI in education based on the TAM variables and the Trust-Risk framework?

Results

Summary Statistics

Table 1 illustrates the summary statistics of the variables in the study. In Table 1, the mean is in the 2 to 3 range for all variables except for Trust. Relative to other variables, Trust exhibits a higher mean performance, and higher scores are associated with lower trust.

Table 1: Descriptive Statistics

DESCRIPTIVES
/VARIABLES= AOAVG EAVG SEAVG PUAVG PEOUAVG ATU_AVG BIAVG TAVG RAVG
/STATISTICS=MEAN STDDEV RANGE VARIANCE KURTOSIS SKEWNESS.

Descriptive Statistics

	N	Mean	Std Dev	Variance	Kurtosis	S.E. Kurt	Skewness	S.E. Skew	Range
AOAVG	41	3.17	.92	.84	2.61	.72	1.09	.37	4.50
EAVG	41	2.79	1.16	1.34	.62	.72	.82	.37	5.00
SEAVG	41	2.93	1.42	2.03	1.91	.72	1.27	.37	6.00
PUAVG	41	3.37	1.59	2.54	.05	.72	.71	.37	6.00
PEOUAVG	41	2.54	1.03	1.07	1.84	.72	.71	.37	5.00
ATU_AVG	41	3.50	1.56	2.42	.19	.72	.75	.37	6.00
BIAVG	41	3.27	1.58	2.49	.55	.72	.82	.37	6.00
TAVG	41	4.90	1.54	2.36	-.45	.72	-.43	.37	6.00
RAVG	41	2.48	1.16	1.35	-.82	.72	.47	.37	4.00
Valid N (listwise)	41								
Missing N (listwise)	0								

RQ1: How does GenAI Orientation influence PU, PEOU, ATU, BI, Trust, and Risk?

High Artificial Intelligence orientation is defined as respondents who, on average, agree with the AI orientation questions.

Based on the results of the Levene's Test for equality of variance, PU, ATU, and BI require the equal variance not assumed version of the t-test. Based on the resulting p-value, no variables were significant. The independent-samples t-test for equality of means indicates there is a non-significant difference between those with high AI orientation (AO) and those with low AO. AI Orientation as a pre-disposition that impacts TAM variables or Trust and Risk was not supported in this exploratory study, as we found no significance. It may be the result of our survey population which consists of Information Technology students who are also digital natives based on their age demographic.

RQ2: How does Self-Efficacy for GenAI in education impact PU, PEOU, ATU, BI, T, and Risk (adapted from Bandura (1977) and Compeau & Higgins (1995) and extended as a determinant of PEOU by Venkatesh (2000)).

Based on t-test group statistics as illustrated in Table 2, those with low Self-Efficacy demonstrate the highest average means for PU, ATU, and Trust, and higher scores are associated with a lower measurement of the variable. In other words, low Self-Efficacy means lower Perceived Usefulness, Attitude Toward Use, and Trust.

Table 2: T-test by GenAI in Education SE (Self-Efficacy)

Group Statistics						
		SE	N	Mean	Std. Deviation	Std. Error Mean
PUAVG		0 (low)	8	5.292	1.201	0.425
		1(high)	33	2.899	1.308	0.228
PEoUAVG		0 (low)	8	3.625	1.119	0.396
		1(high)	33	2.273	0.831	0.145
ATU_AVG		0 (low)	8	4.750	1.648	0.583
		1(high)	33	3.197	1.397	0.243
BIAVG		0 (low)	8	4.375	1.385	0.490
		1(high)	33	3.000	1.521	0.265
TAVG		0 (low)	8	5.800	1.318	0.466
		1(high)	33	4.685	1.5248	0.2654
RAVG		0 (low)	8	2.625	1.4675	0.5188
		1(high)	33	2.448	1.1012	0.1917

Based on the Levene's Test for equality of variance (see appendix), no variables require the equal variance not assumed version of the t-test (Arkkelin, 2014). As illustrated in Table 3, an independent-samples t-test (two-tailed) demonstrates that Self-Efficacy has a statistically significant effect on the TAM variables PU, PEoU, ATU, and BI. However, Self-Efficacy's effect on Trust and Risk is non-significant. SE is a determinant of PEoU based on Venkatesh and Bala (2008), so the effect on PEoU is expected.

Table 3: Independent-samples T-test by GenAI in Education SE (Self-Efficacy)

Independent Samples Test									
t-test for Equality of Means									
		t	df	Significance		Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
				One-Sided p	Two-Sided p			Lower	Upper
PUAVG	Equal variances assumed	4.708	39.000	<.001	<.001	2.393	0.508	1.365	3.421
PEoUAVG	Equal variances assumed	3.857	39.000	<.001	<.001	1.352	0.351	0.643	2.061
ATU_AVG	Equal variances assumed	2.727	39.000	0.005	0.010	1.553	0.570	0.401	2.705
BIAVG	Equal variances assumed	2.330	39.000	0.013	0.025	1.375	0.590	0.182	2.568
TAVG	Equal variances assumed	1.899	39.000	0.032	0.065	1.115	0.587	-0.072	2.303
RAVG	Equal variances assumed	0.381	39.000	0.353	0.705	0.177	0.463	-0.760	1.113

RQ3: How does Experience (E) with GenAI in education impact PU, PEoU, ATU, BI, T, and Risk, as adapted from Sukirman et al. (2024)?

As illustrated in Table 4, based on t-test group statistics, those with low Experience demonstrate a higher average mean for PU, ATU, BI, and Trust, and higher scores are associated with lower PU, ATU, BI, and

Trust. This means that students who report lower Experience also report lower Perceived Usefulness, Attitude toward Use, Behavioral Intent, and Trust.

Table 4: T-test by GenAI in Education Experience

Group Statistics					
	E	N	Mean	Std. Deviation	Std. Error Mean
PUAVG	0(low)	9	5.148	1.482	0.494
	1(high)	32	2.865	1.238	0.219
PEoUAVG	0(low)	9	3.519	1.082	0.361
	1(high)	32	2.260	0.846	0.149
ATU_AVG	0(low)	9	5.500	1.392	0.464
	1(high)	32	2.938	1.068	0.189
BIAVG	0(low)	9	5.296	1.379	0.460
	1(high)	32	2.698	1.092	0.193
TAVG	0(low)	9	6.067	1.265	0.422
	1(high)	32	4.575	1.461	0.258
RAVG	0(low)	9	2.400	1.393	0.464
	1(high)	32	2.506	1.114	0.197

Based on the results of the Levene's Test for equality of variance (see appendix), no variables require the equal variance not assumed version of the t-test (Arkkelin, 2014). In Table 5, an independent-samples t-test (two-tailed) demonstrates that Experience has a statistically significant effect on the TAM variables PU, PEoU, ATU, BI, and Trust. However, its effect on Risk is non-significant.

Table 5: Independent samples T-test by Experience

Independent Samples Test									
		t-test for Equality of Means							
		t	df	Significance		Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
				One-Sided	Two-Sided p			Lower	Upper
PUAVG	Equal variances assumed	4.684	39.000	<.001	<.001	2.284	0.487	1.298	3.270
PEoUAVG	Equal variances assumed	3.709	39.000	<.001	<.001	1.258	0.339	0.572	1.944
ATU_AVG	Equal variances assumed	5.946	39.000	<.001	<.001	2.563	0.431	1.691	3.434
BIAVG	Equal variances assumed	5.954	39.000	<.001	<.001	2.598	0.436	1.716	3.481
TAVG	Equal variances assumed	2.779	39.000	0.004	0.008	1.492	0.537	0.406	2.577
RAVG	Equal variances assumed	-0.239	39.000	0.406	0.812	-0.106	0.444	-1.004	0.792

RQ4: Which TAM variables (PU, PEoU, and ATU) impact Behavioral Intent (BI) to use GenAI in education?

To explore RQ4, we employ $PU+PEoU+ATU \rightarrow BI$, as adapted from Davis (1989) with dependent variable BIAVG and predictors ATU_AVG, PEoUAVG, PUAVG.

In Table 6, our R Squared is .784, and the adjusted R Squared is .766, which indicates our model, consisting of ATU, PEoU, and PU, explains 78% of the variation in our dependent variable BI (Llaudet & Imai, 2023).

Table 6: R for Linear Regression by TAM on BI

Model Summary (BIAVG)			
R	R Square	Adjusted R Square	Std. Error of the Estimate
.885a	0.784	0.766	0.763

As illustrated in Table 7, the regression Sum of Squares at 78.053 shows a high level of explanatory power from the model predictors (PU, ATU, PEoU) on the dependent variable, BI. The model also shows there is a high probability that predictors are statistically significant on the dependent variable, BI (Salkind, 2017).

Table 7: Linear Regression Analysis of Variance by TAM on BI

ANOVA (BIAVG)					
	Sum of Squares	df	Mean Square	F	Sig.
Regression	78.053	3	26.018	44.667	<.001b
Residual	21.552	37	0.582		
Total	99.604	40			

In Table 8, Linear Regression Coefficients show that PU and ATU are statistically significant as predictors of BI, and PEoU is non-significant. The finding does not conflict with the Venkatesh and Davis (2000), Davis et al. (1989), or Venkatesh et al. (2003) studies that confirmed PEoU as significant in user adoption, but only as a direct determinant of PU.

Table 8: Linear Regression Coefficients by TAM on BI

Coefficients (BIAVG)					
	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
(Constant)	0.109	0.355		0.306	0.762
PUAVG	0.383	0.147	0.387	2.6	0.013
PEoUAVG	-0.089	0.169	-0.058	-0.523	0.604
ATU_AVG	0.599	0.12	0.591	4.994	<.001

RQ5: What are the primary predictors of Behavioral Intent (BI) to use GenAI in education based on the TAM variables and the Trust-Risk framework?

To investigate RQ5, we utilize $PU+PEoU+ATU+T+R \rightarrow BI$ as adapted from Gefen et al. (2003) and Pavlou (2003) with BIAVG as the dependent variable and predictors of ATU_AVG, PEoUAVG, PUAVG, TAVG, RAVG.

In Table 9, the R Squared value indicates that our model (TAM + Trust and Risk) explains 79.5% of the variation in our dependent variable, BI (Llaudet & Imai, 2023). The Adjusted R of .765 is similar to the value in table 6, indicating that Trust and Risk do not improve the model.

Table 9: R for Linear Regression by TAM + Trust and Risk on BI

Model Summary (BIAVG)			
R	R Square	Adjusted R	Std. Error of the Estimate
.891a	0.795	0.765	0.765

As illustrated in Table 10, the regression Sum of Squares is 79.143, which shows a high level of explanatory power by the predictors in the model (TAM + Trust and Risk) on the dependent variable, BI. The results show the predictors are statistically significant on the dependent variable, BI.

Table 10: Linear Regression Analysis of Variance by TAM + Trust and Risk on BI

ANOVA (BIAVG)					
	Sum of Squares	df	Mean Square	F	Sig.
Regression	79.143	5	15.829	27.076	<.001b
Residual	20.461	35	0.585		
Total	99.604	40			

As illustrated in Table 11, PU and ATU are statistically significant as predictors of BI. PEOU, Trust, and Risk are non-significant. Davis (1989) found PU to have a greater effect on actual usage compared to PEOU. Davis et al. (1989) and Venkatesh et al. (2003) found PEOU to be a direct determinant of PU.

Table 11: Linear Regression Coefficients by TAM + Trust and Risk on BI

Coefficients (BIAVG)					
	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
(Constant)	0.84	0.662		1.269	0.213
PUAVG	0.329	0.155	0.332	2.127	0.041
PEoUAVG	0.021	0.203	0.014	0.104	0.917
ATU_AVG	0.663	0.153	0.655	4.326	<.001
TAVG	-0.145	0.12	-0.142	-1.209	0.235
RAVG	-0.137	0.145	-0.101	-0.946	0.351

Multicollinearity

Multicollinearity was assessed in the TAM variables on GenAI in education based on our results and prior studies where PEOU was removed from the model due to multi-collinearity with PU (Subramanian, 1994). As illustrated in Table 12, there is high correlation across independent variables that suggests a strong linear relationship which may indicate potential multi-collinearity: PEOU $\rightarrow$ PU = .718, ATU $\rightarrow$ PU = .758,

T $\rightarrow$ ATU = .731. Table 12 shows that PEOU is non-significant, while PU and ATU are significant on BI. However, table 14, VIF does not show multi-collinearity for PEOU.

Table 12: Correlation across PU, PEOU, ATU, BI, Trust, and Risk

Correlations					
	PUAVG	PEoUAVG	ATU_AVG	BIAVG	TAVG
PUAVG	--				
PEoUAVG	.718**	--			
ATU_AVG	.758**	.485**	--		
BIAVG	.793**	.506**	.856**	--	
TAVG	.517**	.335*	.731**	.561**	--
RAVG	-0.278	0.158	-.461**	-.426**	-.476**

Table 13: Correlation Coefficients across PU, PEOU, ATU, Trust, and Risk on BI

Coefficients (BI AVG)					
	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
(Constant)	0.84	0.662		1.269	0.213
PUAVG	0.329	0.155	0.332	2.127	0.041
PEoUAVG	0.021	0.203	0.014	0.104	0.917
ATU_AVG	0.663	0.153	0.655	4.326	<.001
TAVG	-0.145	0.12	-0.142	-1.209	0.235
RAVG	-0.137	0.145	-0.101	-0.946	0.351

Table 14: Collinearity Statistics

	Correlations			Collinearity Statistics	
	Zero-order	Partial	Part	Tolerance	VIF
(Constant)					
PUAVG	0.793	0.338	0.163	0.241	4.154
PEoUAVG	0.506	0.018	0.008	0.332	3.012
ATU_AVG	0.856	0.59	0.331	0.256	3.902
TAVG	0.561	-0.2	-0.093	0.427	2.342
RAVG	-0.426	-0.158	-0.072	0.514	1.944

Regression

In order to confirm our regression results using the composite score of the average of the latent indicators, we employed a second approach based on the composite latent score using a PLS approach to regression

followed by a basic structural equation model. The latent score is calculated via the weighted sum of its manifest variables. As opposed to the average composite score, latent scores are optimized via an 1) inner approximation, followed by 2) outer approximation, then 3) weight estimation, and finally 4) convergence (Hair et al., 2022; Rigdon, 2014). The latent scores become a weighted composite score.

In reviewing the summary coefficients in table 15, we see that PEOU did not realize significance confirming our previous results. As seen in table 16, the summary Anova illustrates our regression model is statistically significant. Reference table 17 to observe model significant with an R^2 of 0.785 and adjusted R^2 of 0.768 which is similar to the result obtained in the seminal TAM paper (Davis, 1989, p. 332) where we see an R^2 of .74 for the Study 2 pooled result. We see the multicollinearity diagnostics in table 19 which reveal acceptable levels of variance inflation factor (VIF) with only moderate correlations revealed in the data. Figure 1 illustrates the regression scores as calculated by SmartPLS 4.0. The PLS-SEM results confirm that ATU has a positive and statistically significant effect on BI ($\beta = 0.596$, $p = 0.00$), thereby supporting H2: ATU will positively influence BI.

Table 15: Summary coefficients

	Unstandardized coefficients	Standardized coefficients	SE	T value	P value	2.5 %	97.5 %
LV scores - ATU	0.596	0.596	0.118	5.060	0.000	0.358	0.835
LV scores - PEOU	-0.065	-0.065	0.114	0.572	0.571	-0.295	0.165
LV scores - PU	0.388	0.388	0.150	2.581	0.014	0.084	0.693
Intercept	-0.000	0.000	0.076	0.000	1.000	-0.154	0.154

Table 16: ANOVA table

	Sum square	df	Mean square	F	P value
Total	41.000	40	0.000	0.000	0.000
Error	8.798	37	0.238	0.000	0.000
Regression	32.202	3	10.734	45.143	0.000

Table 17: R^2 and adjusted R^2

	LV scores - BI
R-square	0.785
R-square adjusted	0.768
Durbin-Watson test	1.673

Table 18: Multicollinearity Diagnostics

	VIF
LV scores - ATU	2.395

LV scores - PEOU	2.233
LV scores - PU	3.903

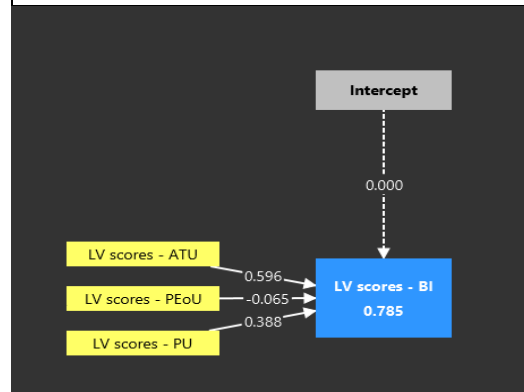


Figure 1: Regression Scores calculated by SmartPLS

Limitations and Further Research

Limitations include a survey pool of 41 undergraduate IT students, a focus on GenAI adoption in education, and limits on studied variables and the impact of determinants and antecedents. Experience was self-reported versus actual. The survey pool could be expanded to other populations to verify if the results generalize. The specific focus on GenAI adoption is relevant, but our study may not extend to on-the-job training which may be important to businesses. Understanding the variables that influence Behavioral Intent (BI) in GenAI Adoption is important, including indirect determinants and antecedents. For example, since ATU and PU are predictors of BI, further study of ATU determinants and predictors specific to GenAI adoption is warranted. Since Self-Efficacy may be domain specific, despite the complexity of general computer self-efficacy versus task-specific self-efficacy, and Trust shows evidence of this as well (Lin & Powell, 2026; Marakas et al., 2007; Venkatesh & Bala, 2008), further study may be informative.

Conclusion

This exploratory study extends Technology Acceptance Model (TAM), Trust-Risk framework, and user disposition to GenAI in education to assess if classic adoption relationships apply to GenAI in education. Consistent with seminal TAM findings (Davis, 1989), results show that Perceived Usefulness and Attitude toward Use are significant predictors of Behavioral Intent. In fact, TAM on BI to use GenAI in education explains 78.5% of variance, comparable to the 74% reported in Davis's (1989) pooled Study2. This may be significant as TAM is applied to GenAI with its unique characteristics. While later TAM iterations removed ATU, ATU's significance in our study aligns with modern e-learning research where ATU demonstrates significance (Gong et al., 2025; Mailizar et al., 2021; Mustofa et al., 2025).

Importantly, Trust significantly influences ATU, demonstrating its importance for educational implications. Conversely, PEOU lacks a direct effect on ATU or BI, but does predict PU, consistent with Davis et al. (1989), Venkatesh and Davis (2000), and Venkatesh et al. (2003). Prior studies indicate that the more experience a user has with an application, the less impact Perceived Ease of Use has (Davis et al., 1989; Adams et al., 1992). Our participants do report a high median level of experience, though other studies evaluated actual experience instead of reported experience (Venkatesh & Bala, 2008).

AI Orientation is a user disposition variable that does not show significance on BI. This may be partly due to the survey demographic of digital natives in IT field of study. Self-Efficacy has a statistically significant effect on the TAM variables PU, PEOU, ATU, and BI. However, Self-Efficacy's effect on Trust and Risk is non-significant. SE is an expected determinant of PEOU based on Venkatesh and Bala (2008).

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Appendix A

GenAI in IT Education Survey questions

7 point Likert scale from survey. Note that agree is low (1,2,3) and disagree is high (7,6,5)

Construct	Code	Survey Question	Source
Artificial Intelligence Orientation	AO1	I read Generative AI bulletins or newsletters.	Ng et al. (2009), adapted from
	AO2	I am concerned about Generative AI incidents and try to take action to prevent them.	Ng et al. (2009), adapted from
	AO3	I am interested in information about Generative AI	Ng et al. (2009), adapted from
	AO4	I am constantly mindful about Generative AI.	Ng et al. (2009), adapted from
Experience	E1	Based on my previous experience, I feel comfortable using Generative AI technology for learning.	Sukirman et al. (2024)
	E2	My experience with using Generative AI or similar tools has influenced my perception of their effectiveness in learning.	Sukirman et al. (2024)
Self-Efficacy	I could complete the class assignment using Generative AI as a tutor:		Compeau & Higgins (1995), adapted from
	SE1	Compeau & Higgins (1995), adapted from	Compeau & Higgins (1995); Venkatesh, 2000

	SE2	...if I had never used a package like it before. (2)	Compeau & Higgins (1995), adapted from
	SE3	...if I could call someone for help if I got stuck. (3)	Compeau & Higgins (1995), adapted from
	SE4	...if I had a lot of time to complete the assignment for which the software was provided. (4)	Compeau & Higgins (1995), adapted from
	SE5	...if I had just the built-in help facility for assistance. (5)	Compeau & Higgins (1995), adapted from
Perceived Usefulness	PU1	Using the Generative AI increases my productivity in this assignment.	Davis (1989)
	PU2	Using the Generative AI enhances my effectiveness in this assignment.	Davis (1989)
	PU3	I find the Generative AI to be useful in this assignment.	Davis (1989)
Perceived Ease of Use	PEoU1	My interaction with the Generative AI is clear and understandable	Davis (1989)
	PEoU2	I find the Generative AI to be easy to use	Davis (1989)
	PEoU3	I find it easy to get the Generative AI to do what I want it to do.	Davis (1989)
Attitude Toward Use	ATU1	I like the idea of using Generative AI in learning.	Venkatesh et al. (2003)
	ATU2	Using Generative AI in learning is a good idea.	Venkatesh et al. (2003)
Behavioral Intention	BI1	I intend to use Generative AI.	Venkatesh et al. (2003)
	BI2	I predict I would use Generative AI.	Venkatesh et al. (2003)
	BI3	I plan to use Generative AI in the near future.	Venkatesh et al. (2003)

Trust	T1	Generative AI are trustworthy.	Malhotra et al. (2004)
	T2	Generative AI are ones that keeps promises and commitments.	Malhotra et al. (2004)
	T3	Generative AI because they keep my best interests in mind	Malhotra et al. (2004)
	T4	Generative AI would tell the truth and fulfill promises related to my personal information.	Malhotra et al. (2004)
	T5	I trust that Generative AI would keep my best interests in mind when dealing with my personal information.	Malhotra et al. (2004)
Risk Beliefs	R1	It would be risky to give my personal information to Generative AI.	Malhotra et al. (2004)
	R2	There would be high potential for loss associated with giving information to Generative AI.	Malhotra et al. (2004)
	R3	There would be too much uncertainty associated with giving information to Generative AI.	Malhotra et al. (2004)
	R4	Providing Generative AI with information would involve many unexpected problems	Malhotra et al. (2004)
Reverse-Coded	R5	I would feel safe giving information to Generative AI.	Malhotra et al. (2004)

Appendix B

Table B1 Homogeneity of Variance Test by GenAI in Education SE (Self-Efficacy)

Homogeneity of Variance Test		Levene's Test for Equality of Variances	
		F	Sig.
PUAVG	Equal variances assumed	0.076	0.784
PEoUAVG	Equal variances assumed	0.321	0.574
ATU_AVG	Equal variances assumed	0.838	0.365
BIAVG	Equal variances assumed	0.082	0.776
TAVG	Equal variances assumed	0.671	0.418
RAVG	Equal variances assumed	2.572	0.117

Based on the Levene's Test for equality of variance, as illustrated in Table B1 no variables require the equal variance not assumed version of the t-test (Arkkelin, 2014).

Table B2: Homogeneity of Variance Test by GenAI in Education Experience

Homogeneity of Variance Test			
		Levene's Test for Equality of Variances	
		F	Sig.
PUAVG	Equal variances assumed	1.356	0.251
PEoUAVG	Equal variances assumed	0.21	0.649
ATU_AVG	Equal variances assumed	1.706	0.199
BIAVG	Equal variances assumed	2.504	0.122
TAVG	Equal variances assumed	0.431	0.515
RAVG	Equal variances assumed	1.541	0.222

Based on the results of the Levene's Test for equality of variance depicted in Table B2, no variables require the equal variance not assumed version of the t-test (Arkkelin, 2014).