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Exploring Drivers of ChatGPT Adoption among Vietnamese University Students

Nguyen Ngoc Quynh Anh

The American School (TAS), Vietnam Email: samynguyen2010@gmail.com

Abstract: *This study exhaustively examines the determinants of university students' behavioral intention to utilize ChatGPT for learning, through the extension of the Technology Acceptance Model (TAM) via the integration of constructs from the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) alongside empirical results on the frequency of past use, on top of basic demographic determinants. A large dataset was collected from 664 university students in Hanoi, Vietnam. Using reliability analysis, Exploratory Factor Analysis (EFA), and Structural Equation Modeling (SEM), the study validates the measures and strictly tests the hypothesized theoretical relationships. Key findings of the study are that perceived usefulness, perceived ease of use, and the frequency of prior ChatGPT use have a significant positive impact on students' behavioral intention. Unexpectedly, year, gender, and perceived risk did not have a significant effect on adoption intention. These results not only validate current TAM assumptions but also carry them further by providing empirical proof of AI tool adoption within the tertiary education sector of an emerging economy. The study has significant theoretical implications in its study of how the determinants interact with each other in a new setting and presents practical guidance to policymakers and teachers who are interested in achieving the greatest use of AI and adoptable technology in schools.*

Keywords: ChatGPT adoption; Technology Acceptance Model (TAM); Structural Equation Modeling (SEM); AI in education; Educational technology

1. Introduction

The rapid adoption of Artificial Intelligence (AI) in tertiary institutions is transforming the interaction of students with learning materials and activities at its core. Among such technologies, ChatGPT, an advanced language model created by OpenAI, has been in the news for its diverse applications in educational settings, from essay composition and descriptive concepts to crafting study guides. Despite its prevalent use, the determinants of the underlying behaviors driving students to adopt such AI-based learning platforms remain to be adequately explored, in particular in the unique socio-educational contexts of developing nations like Vietnam. A comprehensive understanding of the drivers is crucial for the design of effective education policies, improving access to digital technology, and preventing the likely risks of AI abuse or overuse.

The purpose of this study is to address this crucial research gap by empirically investigating the determinants of university students' intention to use ChatGPT for learning. Extending the widely used Technology Acceptance Model (TAM), this study integrates relevant constructs of the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) and includes the significant impact of historical usage frequency. This augmented model is examined in a rigorous fashion with Structural Equation Modeling (SEM) using a large sample of 664 higher education students from diverse universities across Hanoi, Vietnam. By doing so, this research seeks to present novel empirical evidence on the behavioral dynamics of higher education AI adoption to contribute both to theoretical endeavors and practical implementation efforts.

Research objectives:

1. To identify the determinant factors that affect students' intention to learn from ChatGPT.
2. To examine how perceived usefulness, perceived ease of use, perceived risk, and frequency of use influence ChatGPT adoption.
3. To provide policy suggestions by which AI can be employed efficiently and ethically in higher education.

Research questions:

1. What are the reasons students intend to utilize ChatGPT in their study?
2. Is perceived usefulness a strong predictor of behavioral intention to adopt ChatGPT?
3. Are gender and year in school significant predictors of ChatGPT use?
4. How is past usage frequency associated with sustained behavioral intention?

2. Theoretical framework

This study employs and adapts the Technology Acceptance Model (TAM) initially proposed by Davis (1989), which holds that perceived ease of use (PEOU) and perceived usefulness (PU) are direct predictors for behavioral intention (BI). To increase explanatory power, the model is adapted by incorporating AI-specific constructs like perceived risk (PR) and usage frequency (UF), and guided by UTAUT2 principles (Venkatesh et al., 2012).

- Perceived Usefulness (PU): The belief that ChatGPT enhances academic performance.

- Perceived Ease of Use (PEOU): The belief that it is simple to use ChatGPT with little effort.
- Perceived Risk (PR): The fear of error or academic dishonesty.
- Usage Frequency (UF): How often a participant had used ChatGPT prior to this study.
- Demographic Controls: Academic year and gender.
- Hypotheses:

H1: Perceived usefulness (PU) is positively linked with behavioral intention (BI) to use ChatGPT.

H2: Perceived ease of use (PEOU) has a positive impact on behavioral intention (BI) towards ChatGPT usage.

H3: Perceived ease of use (PEOU) has a positive influence on perceived usefulness (PU) of ChatGPT.

H4: Perceived risk (PR) has a negative influence on behavioral intention (BI) towards ChatGPT usage.

H5: Usage Frequency (UF) has a positive impact on behavioral intention (BI) to use ChatGPT.

H6: Gender has no influence on behavioral intention (BI) to use ChatGPT.

H7: The academic year has no significant influence on behavioral intention (BI) to use ChatGPT.

4. Methodology

Survey Sample Statistics

The survey found a significant gender gap among the respondents:

- Male students were in the lead at 84.3% (560 students).
- Female students made up 15.7% (104 students).

This difference could suggest that male students are possibly more interested in or have greater access to ChatGPT than female students in Hanoi universities.

Distribution by Academic Year

Students from different academic years participated in the survey, the most dominant groups of which were:

- Third-year students: 41.9%
- Fourth-year students: 28.5%
- Second-year students: 23.9%

On the other hand, first-year students were represented by only 5.3%, and fifth-year students by just 0.5%. This split shows that students in advanced-level courses (second, third, and fourth years) may be more likely to employ aid tools like ChatGPT. First-year students may not have known that they required such tools yet, or may know them less well, and fifth-year students will have already acquired strong study habits and will be less reliant on new technology. These trends do provide some indication of ChatGPT adoption rates for the different years of university education.

ChatGPT Usage Frequency

The study also found the frequency at which ChatGPT is utilized to learn:

- "Invited" usage: Highest with 45.2% (300 students).
- "Regularly weekly" usage: Second highest with 34.9% (232 students).
- "Regularly daily" usage: 12% (80 students), thus establishing that there are many who have made ChatGPT part of learning efforts on a daily basis.

Surprisingly, very few students reported never or seldom using ChatGPT (0.9%, or 6 students), or using it occasionally (6.9%, or 46 students). Such widespread use attests to the growing popularity of using ChatGPT as a study aid, helping to recall information, solve problems, and gain efficiency in learning. Variations in levels of use across groups illustrate varying individual learning needs, familiarity with technology, and personal views on the usability of ChatGPT in influencing how students use the tool.

4. Survey Results Analysis

Cronbach's Alpha Reliability Test

Table 1: *Cronbach's Alpha Coefficient of Perceived Usefulness Factor (Source: Data processing)*

Variable	Number of observations	Sign	Item-Total Correlation	Corrected Item-Total Correlation	Average Inter-Item Covariance	Cronbach's Alpha
SHI1	664	+	0.746	0.698	0.373	0.905
SHI2	664	+	0.765	0.720	0.371	0.904
SHI3	664	+	0.773	0.729	0.371	0.904
SHI4	664	+	0.760	0.715	0.373	0.905

Table 1 shows that the Cronbach's Alpha coefficient for the Perceived Usefulness scale was 0.905, which is higher than the minimum threshold of 0.7, hence guaranteeing high reliability. The other items' inter-correlation between variables was 0.698 to 0.729, hence indicating high compatibility with the overall scale. The average covariance between variables was 0.371 to 0.373, indicating consistency in the variables. When removing all the variables, Cronbach's Alpha coefficient was also high, indicating that all the variables did not bring down the reliability of the scale.

Table 2: *Cronbach's Alpha Coefficient for the Perceived Ease of Use Factor (Source: SPSS data processing)*

Variable	Number of	Sign	Item-Total	Corrected Item-Total	Average Inter-Item	Cronbach's Alpha

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	observations		Correlation	Correlation	Covariance	
DSD1	664	+	0.635	0.571	0.385	0.909
DSD2	664	+	0.660	0.602	0.384	0.908
DSD3	664	+	0.714	0.665	0.380	0.906
DSD4	664	+	0.640	0.575	0.383	0.909

Table 2 shows that the Cronbach's Alpha coefficient for the Perceived Ease of Use scale was 0.909, which is more than 0.7, confirming the high reliability of the scale. The corrected item-total correlations for the remaining variables ranged from 0.571 to 0.665, indicating high compatibility with the overall scale. The mean covariance between the variables was between 0.380 and 0.385, and this is the highest among the variables. After the removal of each item, the Cronbach's Alpha coefficient was not significantly impacted and was well above 0.908, suggesting that none of the items negatively impacted the reliability of the scale. Such a result means that the Perceived Ease of Use scale is very reliable and can be used in future research.

Table 3: *Cronbach’s Alpha Coefficient for the Perceived Risk Factor (Source: Data processing)*

Variable	Number of observations	Sign	Item-Total Correlation	Corrected Item-Total Correlation	Average Inter-Item Covariance	Cronbach’s Alpha
NTRR 1	664	+	0.433	0.356	0.407	0.915
NTRR 2	664	+	0.425	0.354	0.407	0.9156
NTRR 3	664	+	0.507	0.436	0.400	0.913
NTRR 4	664	+	0.475	0.398	0.402	0.914

Table 3 shows that the Cronbach's Alpha coefficient for the Perceived Risk scale achieved a value of 0.9156, which is higher than the baseline requirement of 0.7, thereby establishing the scale's reliability. Similarly, the corrected item-total correlations for the other items ranged between 0.354 to 0.436. While lower than other scales, these values still indicate a sufficient level of compatibility with the overall scale. The average covariance among the variables varied from 0.400 to 0.405. This indicates a moderate, not minimal, degree of compatibility among the items. Upon deletion of each variable, the Cronbach's Alpha coefficient did not vary remarkably but remained higher than 0.913, which indicates that none of the items negatively impacted the reliability of the scale. This result indicates that the Perceived Risk scale is highly reliable and can be used for subsequent analyses.

Table 4: *Cronbach’s Alpha Coefficient for the Behavioral Intention Factor (Source: Data processing)*

Variable	Number of Observations	Sign	Corrected Item-Total Correlation	Corrected Item-Total Correlation	Average Inter-Item Covariance	Cronbach’s Alpha
YĐH V1	664	+	0.747	0.702	0.376	0.905
YĐH V 2	664	+	0.775	0.733	0.373	0.904
YĐH V 3	664	+	0.783	0.743	0.372	0.904
YĐH V 4	664	+	0.686	0.625	0.377	0.907

Table 4 shows that the Cronbach's Alpha for the Behavioral Intention scale is 0.9074, much higher than the typical 0.7, which specifies high reliability. The item-total correlations vary from 0.625 to 0.743, which are in very high correlation with the total scale. The mean inter-item covariance varies between 0.372 and 0.377, indicating a good level of consistency within the scale. Interestingly, as each item is deleted one by one, Cronbach's Alpha remains stable but always more than 0.904, thereby further supporting that all the items make a positive contribution towards the scale. The results confirm that the Behavioral Intention scale is highly reliable and may be utilized for further analysis.

Overall, the Behavioral Intention scale is equally good in terms of reliability, accurately capturing students' readiness and intention to use ChatGPT for learning. Therefore, the scale is entirely fit for further use in future research analysis.

Exploratory Factor Analysis (EFA)

After assessing the reliability of the scale components using Cronbach’s Alpha, the study proceeded with Exploratory Factor Analysis (EFA). The purpose of EFA is to identify the underlying factors that truly represent the observed variables within the scales.

Table 5: *Exploratory Factor Analysis (EFA) Table Using the Principal Component Analysis Method (Source: Data processing)*

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor 1	7.261	4.441	0.454	0.454
Factor 2	2.819	1.052	0.176	0.630
Factor 3	1.768	0.747	0.111	0.741

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Factor 4	1.020	0.554	0.064	0.804
Factor 5	0.467	0.057	0.029	0.833
Factor 6	0.410	0.032	0.026	0.859
Factor 7	0.378	0.076	0.024	0.883
Factor 8	0.302	0.022	0.019	0.902
Factor 9	0.280	0.025	0.018	0.919
Factor 10	0.255	0.012	0.016	0.935
Factor 11	0.243	0.035	0.0152	0.950
Factor 12	0.208	0.016	0.013	0.963
Factor 13	0.194	0.040	0.012	0.975
Factor 14	0.152	0.010	0.010	0.985
Factor 15	0.142	0.039	0.010	0.994
Factor 16	0.104	-	0.010	1.000

Table 5 presents the results of the Exploratory Factor Analysis (EFA) using the Principal Component Analysis (PCA) method. The results indicate that while there were initially 16 factors, only 4 principal components were extracted based on the Kaiser criterion (Eigenvalue > 1). The total cumulative variance explained by these four factors is 80.42%, demonstrating that they account for the majority of the data variability and provide a high level of representativeness for the research model.

Factor 1 has an Eigenvalue of 7.261, explaining the highest proportion of variance (45.38%), indicating it is the most significant factor. Factor 2, Factor 3, and Factor 4 reflect 17.62%, 11.05%, and 6.38% of the variance, respectively, which gives an aggregate variance explained of 80.42%, thus well within the boundary set for factor analysis. All other factors from Factor 5 and beyond have Eigenvalues less than 1 and represent a very low level of the variance (below 5%). These factors were not included in the model.

The large discrepancy in eigenvalues between Factor 1 (7.261) and Factor 2 (2.819) indicates that the first factor is significantly more important than the remaining factors. Additionally, the decreasing differences between subsequent factors confirm that only the first four factors have substantial significance in the model. This result demonstrates that the Exploratory Factor Analysis (EFA) has effectively grouped the observed variables and contributed to optimizing the research model.

Table 6: *Factor loadings matrix (Source: Data processing)*

Variable	Factor1	Factor2	Factor3	Factor4	Uniqueness
YĐHV 1	0.780	-0.028	-0.288	0.396	0.151
YĐHV 2	0.808	-0.022	-0.305	0.337	0.140
YĐHV 3	0.815	-0.073	-0.195	0.364	0.159
YĐHV 4	0.713	-0.215	-0.004	0.401	0.285
SHI 1	0.766	0.1156	-0.353	-0.387	0.126
SHI 2	0.784	0.126	-0.347	-0.388	0.099
SHI 3	0.807	-0.077	-0.218	-0.225	0.245
SHI 4	0.781	0.110	-0.345	-0.242	0.200
DSD 1	0.650	-0.378	0.479	-0.103	0.196
DSD 2	0.677	-0.392	0.504	-0.069	0.130
DSD 3	0.733	-0.329	0.412	-0.112	0.173
DSD 4	0.659	-0.394	0.448	-0.072	0.205
NTRR 1	0.335	0.730	0.175	-0.027	0.323
NTRR 2	0.319	0.693	0.342	0.103	0.291
NTRR 3	0.405	0.760	0.256	0.042	0.191
NTRR 4	0.370	0.754	0.273	0.027	0.219

The results show that the observed variables have high factor weights on one main factor, while having lower weights on the remaining factors, demonstrating that factor analysis has helped to classify the variables clearly.

The variables in the Behavioral Intention group (YĐHV1-YĐHV4) all have high weights on Factor 1, ranging from 0.713 to 0.815, indicating that this factor represents well the group of variables on students' intention to use ChatGPT. Similarly, the variables in the Perceived Usefulness group (SHI1 - SHI4) also have high weights on Factor 1, with values ranging from 0.766 to 0.807, which confirms that the perceived usefulness of ChatGPT is closely related to the intention to use.

The variables in the Perceived Ease of Use group (DSD1 - DSD4) have high weights on Factor 3, ranging from 0.412 to 0.504, indicating that students consider the ease of use of ChatGPT to be an important factor, but the level of contribution is not too strong compared to other factors. The Perceived Risk category (NTRR1-NTRR4) also has high values on Factor 2, from 0.693 to 0.760, indicating that students' perceived risk has a significant influence over their adoption of ChatGPT. The Uniqueness column informs us about the proportion of variance not captured by general factors. Variables with low Uniqueness (< 0.2), such as SHI2 (0.099), SHI1 (0.126), YĐHV2 (0.140), show that they are well explained by the factor model. On the contrary, variables with high Uniqueness (> 0.3), such as NTRR1 (0.323), NTRR2 (0.291), show that they may be influenced by factors other than those retained in the analysis. In general, the results of factor analysis show that the model has grouped the observed variables into each factor reasonably, ensuring consistency in the scale. This result helps confirm that the factors Behavioral Intention, Perceived Usefulness, Perceived Ease of Use, and Perceived Risk play an important role in students' decisions to use ChatGPT, and at the same time provides a solid basis for further analysis in the study.

Table 07: *Variance explained by factors (Source: Data processing)*

Factor	Variance	Difference	Proportion	Cumulative
Factor1	3.521	0.252	0.220	0.220
Factor2	3.269	0.203	0.204	0.424
Factor3	3.066	0.054	0.192	0.616
Factor4	3.011	-	0.188	0.804

Table 07 presents the variance accounted for by factors in exploratory factor analysis (EFA). It is seen that four factors have been extracted, which account for a cumulative variance of 80.42%, which means that the factors explained 80.42% of data variation, which is of very high significance in the research. Factor 1 accounted for most of the variance (3.521), which was 22.01% of the total variance, indicating that this factor was the most influential factor in the model. Factor2 and Factor 3 accounted for 20.43% and 19.16% of variance, respectively, and the cumulative variance reached 61.60%, indicating that the first three factors had an important role to play in explaining the data. Factor4, which had the lowest explained variance (18.82%), still accounted for a significant proportion of total cumulative variance. Variance difference between the factors is presented in the Difference column, where the difference between Factor1 and Factor2 is 0.252, between Factor2 and Factor3 is 0.203, and between Factor3 and Factor4 is merely 0.054, hence showing the decreasing contribution of the factors. This result guarantees that the factors obtained are vital in the explanation of the data and aid in creating a robust research model.

Table 08: *Rotated Factor Loadings Matrix (Source: Data processing)*

Variable	Factor1	Factor2	Factor3	Factor4	Uniqueness
YĐHV1			0.832		0.151
YĐHV2			0.808		0.1395
YĐHV3			0.802		0.159
YĐHV4			0.724		0.285
SHI1		0.874			0.126
SHI2		0.883			0.100
SHI3		0.709			0.245
SHI4		0.787			0.200
DSD1	0.867				0.196
DSD2	0.900				0.130
DSD3	0.844				0.173
DSD4	0.853				0.205
NTRR1				0.801	0.323
NTRR2				0.835	0.291
NTRR3				0.882	0.191
NTRR4				0.872	0.219

Table 08 presents the rotated factor loadings, which represent levels of correlation between observed variables and latent factors after conducting Exploratory Factor Analysis (EFA). As can be seen, the variables are converged into four main factors. Specifically, the items of Behavioral Intention (YĐHV) load highly on Factor 3 with coefficients ranging from 0.724 to 0.832, indicating a high correlation with the third factor. Similarly, Social Influence (SHI) items loaded strongly on Factor 1, 0.709-0.883, which means that the SHI group is strongly represented by Factor 1. Items from Perceived Usefulness (DSD) also loaded strongly on Factor 1, 0.844-0.900, which shows that the first factor is strongly represented by this group.

Lastly, Facilitating Conditions (NTRR) all factor highly on Factor 2, 0.801 to 0.882, and this would imply that this set of variables is best captured by the second factor. Second, the "Uniqueness" column shows the percentage of each variable's variance not explained by the factors extracted. The uniqueness values are low (below 0.3) for most variables, which means that most of the variance of observed variables is accounted for by factors extracted. The EFA outcomes overall suggest a clear grouping of variables, and factor loadings are in desirable values, fulfilling both convergent and discriminant validity for factor analysis.

Table 09: *Factor rotation matrix (Source: Data processing)*

Factor	Factor1	Factor2	Factor3	Factor4

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Factor1	0.531	0.571	0.559	0.282
Factor2	-0.455	0.089	-0.096	0.879
Factor3	0.695	-0.157	-0.324	0.380
Factor4	-0.154	-0.631	0.757	0.066

Table 09 shows the rotated factor matrix that clarifies the factor relationship by rotating its loadings for easier interpretation. It can be observed from the results that Factor 1 has relatively high loadings on the other factors (0.531, 0.571, 0.559), indicating that it is highly correlated with more than one observed variable. Factor 2 gets its highest loading at 0.879, while Factor 3 gets a maximum loading of 0.695, and Factor 4 has a salient value of 0.757, suggesting that each factor has a distinctive contribution to the model in general.

Regression Analysis

After ensuring the reliability of the measurement scales and performing exploratory factor analysis (EFA), multiple linear regression analysis was performed in the research to examine the influence of various factors on students' intention to utilize ChatGPT in learning. Multiple linear regression was employed to provide the association between the dependent variable and the independent variables in the research model.

The results of regression analysis describe the extent to which each factor influences students' intention, thereby providing a scientific basis for practical recommendations and proposals for enhancing effective utilization of ChatGPT in academic learning.

Table 10: *ANOVA – Model Fit Assessment (Source: Data processing)*

Source	SS	df	MS	Number of obs	664
Model	288.548	6	480.913	F(6, 657)	138.11
Residual	228.781	657	0.3482	Prob > F	0.000
Total	517.328	663	0.780	R-squared	0.558
				Adj R-squared	0.554
				Root MSE	0.590

Table 10 shows the result of the ANOVA test representing regression model fitness in the article "Factors Influencing the Use of ChatGPT in Learning among Students of Hanoi University." Based on the results, F(6, 657) = 138.11 with p-value = 0.000, so the model is statistically significant. This is a sign that one of the independent variables has a considerable influence on students' intention to use ChatGPT in their studies. The R-squared of 0.558 shows that the model accounts for approximately 55.78% of the variance in the dependent variable. That is, the independent factors within the model accounted for over half of the variance in the students' intention to use ChatGPT. The Adjusted R-squared score of 0.554 informs the goodness-of-fit to the model that has been corrected for the number of independent factors. This implies extremely high accuracy.

Further, the Root Mean Square Error (Root MSE) = 0.590 is a residual standard deviation and represents the estimated prediction error of the model on average. Overall, the ANOVA findings confirm the regression model to be statistically significant and with very good explanatory power for explaining the intention of students to use ChatGPT in learning. This provides a good foundation for further investigation of each factor's contribution to the model.

Table 11: *Linear regression results (Source: Data processing)*

YĐHV	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
Gender	0.098	0.063	1.55	0.121	-0.026	0.222
Academic year	0.008	0.027	0.31	0.754	-0.026	0.062
Frequency	0.193	0.029	6.66	0.000	0.136	0.249
SHI	0.472	0.030	15.51	0.000	0.412	0.532
DSD	0.274	0.029	9.42	0.000	0.217	0.331
NTRR	0.039	0.030	1.30	0.194	-0.020	0.098
_cons	0.105	0.163	0.65	0.519	-0.215	0.426

Table 11 shows the result of a linear regression test to determine the impact of various factors towards the intention to use ChatGPT (IU) in learning tasks. From the result, it can be seen that the variables perceived usefulness (PU), frequency of use (frequency), and perceived ease of use (PEOU) have significant impacts on the intention to use ChatGPT with the regression values of 0.472, 0.193, and 0.274, respectively. All three have p-values = 0.000, with strong and statistically significant effects at the 1% level.

This indicates that the greater the students' perception of ChatGPT as useful and convenient to use, the more they use it, the higher the probability of repeating the use of ChatGPT in learning. On the other hand, the perceived risk (PR) variable coefficient is 0.039 but is not statistically significant (p = 0.194), which means the perception of risks involved in using ChatGPT has no effect on students' usage.

Similarly, gender (coefficient = 0.098, p = 0.121) and year of study (coefficient = 0.008, p = 0.754) fail to contribute significantly to the intention to use ChatGPT, which suggests that they do not differ significantly based on gender or year of study in terms of whether they do or do not use the tool.

The constant (_cons) is 0.105 and is not statistically significant (p = 0.519), indicating that at all independent variables being zero, there is no perceived difference in the willingness of students to use ChatGPT.

Based on the above regression analysis results, we can fill in the structural:

SHI (Perceived Usefulness) → YĐHV: 0.472

DSD (Perceived Ease of Use) → YĐHV: 0.274

NTRR (Perceived Risk) → YĐHV: 0.039 (Not statistically significant)

Gender → YĐHV: 0.098 (Not statistically significant) Academic Year → YĐHV: 0.008 (Not statistically significant)

Usage Frequency → YĐHV: 0.1926

Perceived Usefulness
Perceived Ease of Use
0.274***

Behavioral Intention
- Gender (0.098)
- Academic Year (0.008)
- Frequency (0.472***)
Perceived Risk

Note:

***: Significant at the 1% **: Significant at the 5% *: Significant at the 10%

Image 1: Results of the proposed research model

5. Discuss the results of a study

The empirical findings of the present research yield rich information on factors explaining the behavioral intention of university students towards adopting ChatGPT as a study aid. Being consistent with the fundamental premise of the Technology Acceptance Model (TAM), the findings support that perceived usefulness ($\beta = 0.472$, $p < 0.001$) and perceived ease of use ($\beta = 0.274$, $p < 0.001$) are solid positive determinants of students' intention to use ChatGPT. The strong impact of perceived usefulness reaffirms its pivotal role, as defined by Davis (1989), indicating that students are highly inclined to implement ChatGPT if they feel it would enhance their learning efficiency and academic productivity. Similarly, the positive impact of perceived ease of use, as defined by Venkatesh and Davis (2000), focuses on the fact that ChatGPT's usability, quick response times, and minimal technical demands help in its adoption by students.

Apart from these basic TAM constructs, the study in this research also found that the frequency of past behavior ($\beta = 0.193$, $p < 0.001$) has a significant positive impact on action intention. The finding is consistent with Hossain et al. (2019), suggesting that more familiarity and positive experience with ChatGPT strengthen students' intention to utilize it more in their study routine. Regular users have to form a higher understanding of the strengths and weaknesses of ChatGPT, thereby validating the intention for continued use.

Contrary to expectations, perceived risk ($\beta = 0.039$, $p = 0.194$) had no statistically significant effect on students' willingness to use ChatGPT. This finding is contrary to some earlier work (e.g., Featherman & Pavlou, 2003), which highlights the perception of risk as a key deterrent to technology adoption, especially concerning data security and privacy. One probable cause of such a divergence within the Vietnamese educational environment is that students utilize ChatGPT as much of an adjunct tool of study, typically double-checking information, thus shying away from concerns for wholesale accuracy or data sensitivity. Moreover, the very nature of ChatGPT as something of a publicly accessible and often faceless apparatus for academic assistance may vitiate individual perceptions of personal risk compared to monetary or personal data systems.

Additionally, control variables such as gender ($p = 0.121$) and academic year ($p = 0.754$) were not significant influencers of students' intention towards using ChatGPT. This contradicts some existing studies (e.g., Gefen & Straub, 1997), which assumed gender differences in adopting technology. The lack of significance of these demographic variables in our analysis may mean that the extensive use and inclusion of ChatGPT across many disciplines have leveled the playing field in its acceptance, cutting across disciplinary demarcations typical of the university environment. This implies a pattern of more even adoption of AI aids in educational environments, regardless of the demographic profile or academic status of students.

Overall, these findings contribute to the existing TAM body of knowledge by empirically validating its underlying principles in the new context of Vietnamese higher education and AI-based language models. The leading role of previous frequency of use is indicative of the influence of initial positive interactions on long-term adoption. Besides, the nuanced recognition of the non-significant impact of perceived risk and demographics provides a more in-depth contextual understanding of AI adoption behaviors, uncovering the imperative nature of context-based considerations in technology acceptance studies

6. Conclusion

This study could determine the major determinants of the behavioral intention of university students to use ChatGPT for learning in Hanoi, Vietnam. Our extended TAM model confirms that perceived usefulness, perceived ease of use, and frequency of past use are positively significant determinants of adoption intention. Conversely, perceived risk, gender, and academic year were not positively significant determinants of this intention. These findings extend the understanding of AI adoption processes in universities, particularly for developing nations.

7. Practical Implications & Limitations

The findings of this study have several practical implications for the stakeholders of higher education and technology integration. Firstly, universities and educators must make a priority of making efforts that raise students' perceived usefulness of ChatGPT, such as providing good guidelines on how to effectively use it in their learning, showing good examples of integration, and emphasizing how the use of ChatGPT can actually facilitate better learning outcomes without undermining critical thinking. Second, with a focus on perceived ease of use, intuitive interfaces, readily available training facilities, and technical support can minimize adoption barriers. Third, by taking advantage of the power of previous frequency of use, schools and universities can stimulate initial exploratory use through workshops, coursework, or guided exercises to establish familiarity and positive experience and thus long-term adoption. Lastly, although perceived risk did not inhibit adoption in our study, it is prudent for universities to expect ethical concerns, promote responsible AI use, and teach students important critical evaluation of AI-generated content for academic honesty and digital literacy.

Limitations

While having its virtues in positive contribution, there are limitations to this study of interest for future studies. First, its cross-sectional nature limits the scope of inferring causality and making conclusions about temporal changes in the adoption behavior. Future longitudinal studies can potentially provide more insightful viewpoints on the dynamic AI adoption process. Second, the utilization of self-report information might introduce common method bias; the utilization of objective usage information or triangulation of qualitative methods would be capable of boosting validity. Third, the sampling frame was constrained to Hanoi, Vietnam universities, and therefore the generalizability of the findings to other geographical areas or educational institutions could be compromised. Future research can boost the sample to reflect a more extensive range of universities as well as students. Finally, while our expanded TAM model explained a great deal of variance in behavioral intention, other potential influencing variables not included in this study (e.g., social influence from teachers or peers, facilitating conditions, specific AI literacy dimensions beyond general awareness) can be examined in future research.

8. Future Research Directions

Accepting these limitations as a stepping stone, future research can now explore actual usage patterns and academic performance outcomes of ChatGPT adoption. Qualitative research, such as in-depth interviews or focus groups, could provide a better understanding of students' risk perceptions and the multifaceted reasons behind the non-significant influence of demographic variables. Cross-cultural studies in other countries or school systems would also be valuable to establish the cultural generality of our findings. Furthermore, studies on the effects of specific pedagogical methods and teacher guidance on students' productive and responsible application of AI tools for learning environments are welcome.

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