Educational Administration: Theory and Practice
2024, 30(8) 236-251
ISSN: 2148-2403
https://kuey.net/
Research Article

EYE ON AI: Investigating the Intention to Use and Acceptance of Generative Artificial Intelligence in Bulacan State University

Calvin Eladia[1*], Justine Jay Legaspi[2], Monaliza Navarro[3], Trisha Tanig[4], and Valentine Blez Lampayan[5]

[1*,2,3,4,5]Bulacan State University eladiacalvin@gmail.com, legaspijustine24@gmail.com, navarromonalizau7248@gmail.com, tanigtrishad7340@gmail.com ,valentine.lampayan@bulsu.edu.ph

Citation: Calvin Eladia, et.al, (2024), EYE ON AI: Investigating the Intention to Use and Acceptance of Generative Artificial Intelligence in Bulacan State University, *Educational Administration: Theory and Practice*, 30(8), 236-251
Doi: 10.53555/kuey.v30i8.6458

ARTICLE INFO | **ABSTRACT**

Despite the growing prominence of Generative Artificial Intelligence (GenAI) in the education landscape, there is limited research regarding its acceptance in the Philippines. Hence, the researchers studied the intention to use and acceptance of GenAI among college students and educators at Bulacan State University utilizing the constructs from the Unified Theory of Acceptance and Use of Technology framework. The study employed a quantitative approach through a survey questionnaire and interviews to gather actionable insights. Structural Equation Modeling (SEM) was used to investigate how the constructs affect the college students' intention to use and acceptance of GenAI while the Welch's t-test was used to determine if a significant difference exists in their acceptance of GenAI. The findings revealed that 85.84% college students used GenAI while 76.11% educators used the tool. Moreover, both groups demonstrated a moderate knowledge of GenAI's limitations, with Welch's t-test revealing no significant difference exists in their acceptance levels of GenAI. Key findings showcase that effort expectancy and behavioral intention affect the acceptance of college students on GenAI tools, while performance expectancy and facilitating conditions affect their behavioral intention. However, social influence does not significantly affect their intention to use and acceptance of GenAI. Out of all factors, only facilitating conditions displayed a significant total effect on their GenAI acceptance, revealing the importance of the institution's role regarding this technology.

Keywords: GenAI acceptance, behavioral intention, performance expectancy, effort expectancy, social influence, facilitating conditions, knowledge, education landscape

1. Introduction

From traditional chalkboards to interactive virtual whiteboards, an innovative and significant shift has been observed that exemplifies the integration of technology in educational settings. It illustrates the rapid acceleration of technological advancement, and even educational or academic institutions are not subject to exemption. In addition, technology in education is visible as a prevalent matter that navigates society to be fully adept in the ever-changing world.

In the same lens, one of the most transformative technologies in recent years is Artificial Intelligence (AI). As stated by Gerlich (2023), AI has the potential to revolutionize various aspects of our lives, which is significantly visible at the current times. AI was defined as an artificial object that responds to circumstances upon recognition of the situation (Rajendra, Kumari, Rani, Dogra, Boadh, Kumar, & Dahiya, 2022). On the same landscape, Generative AI (GenAI) is a subset of AI systems that is capable of creating and producing output that resembles human-generated materials. These outputs include text, images, videos, music, computer code, or even the merged version of these media (Farrelly & Baker, 2023).

Among the most renowned and widely used GenAI tools nowadays is called ChatGPT (Salinas-Navarro, Vilalta-Perdomo, Michel-Villarreal, & Montesinos, 2024). It is a chatbot tool trained and constructed with hundreds of billions of parameters for comprehending texts that acquire language patterns to provide and generate a logical response (Haglund, 2023; Pinzolits, 2023). It was found that the Philippines topped the list for those who searched for ChatGPT based on interests (Cotton, Cotton, & Shipway, 2023). Other notable GenIAI tools include Gemini, Midjourney, Microsoft New Bing Chat, Dall-E, AudioCraft, and other GenAI technologies. As a result, such tools were now recognized and used worldwide, which caused a significant impact on the landscape of education.

Upon utilizing GenAI tools such as ChatGPT, numerous advantages for both students and educators were identified in the study of Senechal, Ekholm, Aljudaibi, Strawderman, and Parthemos (2023). It was stated that this can help ease the workloads of the teachers and simultaneously offer assistance to students in terms of studying, researching, and writing. Similarly, students' perceptions of GenAI showcased different potential or capabilities of such tools. In the study of Chan and Hu (2023), the students have cited several reasons behind their willingness to use GenAI tools. It includes support, most likely in terms of academic assistance. However, challenges were also mentioned concerning the integration of GenAI tools that need to be discussed thoroughly to maximize the benefits of GenAI tools. Unsettlingly, risks were also identified in the ethical dimension of education. Ethical concerns such as privacy and data security, originality, and academic dishonesty, were highlighted about its possible implications in education (Vaccino-Salvadore, 2023). Schools such as New York City Public Schools and Seattle Public Schools have banned ChatGPT because of possible academic dishonesty in the form of cheating (Johnson, 2023). This has sparked a discussion about whether GenAI tools should be banned permanently or if it is something that can be used as a tool with proper policies and guidelines. In addition, according to UNESCO (2023), upon the expansion of GenAI, educational institutions should insist on regulating the utilization of such tools and should not only rely on corporate creators to manage responsible use. GenAI should be embraced rather than to be avoided for the future of education, as it can be a resource that is useful for both educators and students.

However, in the study of Shaw, Yuan, Brennan, Martin, Janson, Fox, and Bryant (2023), it was found that approximately 50.00% of the students utilize GenAI, while over 75.00% of faculty members do not employ such technologies in higher education. In addition, there exists a 22.00% difference between the percentage of students who use GenAI from the period of spring up to the fall season (Coffey, 2023). It was also stated that students have more chances of adopting it in the form of utilization. A study stated that improving awareness, utilization, and interactive discussions for both educators and learners is much more effective and sustainable rather than banning these GenAI tools in higher education (Lim, Gunasekara, Pallant, Pallant, & Pechenkina, 2023). They added that HEIs should be updated on the current advancements in technology and simultaneously improve their support mechanisms to provide assistance in the usage of GenAI tools. This may include interventions in some dimensions of the AI ecological policy framework that allow comprehensive learning of the implications brought by this progress.

This discussion has led the present researchers to investigate the intention to use and the acceptance of the GenAI in Higher Education Institutions (HEIs). According to Teo (2011), technology acceptance is the first step in adopting a certain technology by predicting the user's intention to use it. However, there is an inadequate amount of studies in the Philippines investigating the intention to use and acceptance of GenAI tools in HEIs to give sufficient insights that will help the development of preemptive measures for the responsible use of the said tool. By investigating this matter, the researchers used relevant information to understand the implications brought by GenAI and suggested actionable insights. Also, variability may arise due to various geographical origins of these previous studies, which may introduce bias given its diverse national background, where the expansion of local study is essential. Also, previous researchers were mainly focused on the viewpoints of students, the study included educators to gain comprehensive understanding of the impact of GenAI technology on education.

On the other hand, Bulacan State University (BulSU) is currently one of the largest HEIs in the Central Luzon Region that also aims to bring forth a relevant quality and accessible education. The university is dedicated to offer education for eligible students, targeting a 21st-century setting for its learning environment. Given this aspiration, it has become essential to examine the readiness of the BulSU community to accept advanced technologies like GenAI, which can support the achievement of its goals and objectives. Therefore, the researchers investigated the intention to use and acceptance of the Bulacan State University community using respondents' performance expectancy, effort expectancy, social influence, and facilitating conditions throughout the study.

1.1 Research Questions

The general problem of this study was to investigate the intention to use and acceptance of Generative Artificial Intelligence (GenAI) among college students and educators.

Specifically, the study sought to answer the following questions:

1. What is the proportion of college students and educators who have used GenAI in terms of their:

1.1 Sex;

1.2 Age; and

1.3 College Affiliation?

2. What is the level of knowledge among college students and educators about the limitations of GenAI?
3. How do the college students and educators be described in terms of their:
3.1 Performance Expectancy;
3.2 Effort Expectancy;
3.3 Social Influence;
3.4 Facilitating Conditions; and
3.5 Behavioral Intention on GenAI?
4. How do the college students' performance expectancy, effort expectancy, social influence, and facilitating conditions affect their intention to use and acceptance of GenAI?
5. Is there a significant difference in the level of GenAI acceptance between college students and educators?
6. What actionable insights can be suggested in higher education institutions concerning the usage of GenAI?

1.2 Significance of the Study

In recent years, the utilization of advanced technologies in education has been a growing trend worldwide. Yet, Bulacan State University (BulSU) has not implemented an official policy on the use of Generative Artificial Intelligence (GenAI). Recognizing this gap, the researchers aim to raise awareness and understanding of GenAI's potential benefits and limitations among college students and educators at BulSU. By examining the factors affecting the acceptance and use of GenAI, this study provides actionable insights that can guide the university in formulating effective policies and support systems. These measures will ultimately enhance the educational experience and foster a technologically adept academic environment.

1.3 Hypotheses of the Study

The research hypothesis has three components based on the statistical treatments used for data analysis in the study. The research hypothesis statements were the following:
1.3.1 *Proportion of who have used Generative Artificial Intelligence (GenAI)*
$H_{o(1)}$: The proportion of the college students and educators who have used GenAI is 50%.
1.3.2 *Structural Equation Modeling Hypothesis on Study's Variables*
$H_{o(2)}$: Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, and Behavioral Intention has no effect on GenAI Acceptance.
$H_{o(3)}$: Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions has no effect on Behavioral Intention.
$H_{o(4)}$: Behavioral Intention does not mediate the effect of Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions on GenAI Acceptance.
$H_{o(5)}$: Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions has no total effect on GenAI Acceptance.
1.3.3 *Difference Between College Students and Educators on GenAI Acceptance*
$H_{o(6)}$: There is no significant difference in the level of GenAI acceptance between college students and educators.

2. Material and Methods

This section discusses the research methods and procedures used to investigate the problems of the study. It includes the research methods, sample of the study, research instruments, and statistical treatments.

2.1 Research Methods

The study employed a quantitative research approach to understand the implications of Generative Artificial Intelligence (GenAI) and suggest actionable insights for its future use. Following Zou and Huang (2023), this approach is objective, focusing on measuring variables using numbers and drawing general conclusions from the data. A descriptive correlation study was used to understand students' characteristics, their intention to use and acceptance of GenAI, and their perception of it at Bulacan State University (BulSU). This type of study, as described by Klainin-Yobas, He, and Lau (2015), assesses the relationship among study variables. The researchers aimed to examine the relationship between performance expectancy, effort expectancy, social influence, facilitating conditions, behavioral intention, and GenAI acceptance. They sought to identify the direct, indirect, and total effects of these factors on GenAI acceptance using a modified survey questionnaire. The study also employed a survey design to collect primary data from all segments of the population (Tanner, 2002).

2.2 Sample of the Study

Participants were selected using a stratified random sampling approach applied to ensure that there was a representative for each college. Cochran's Formula (*CF*) was applied to determine the required respondents. The study incorporated a 20% dropout rate (*DR*) in determining the adjusted sample size for college students and 10% *DR* for educators.

With that, the study surveyed 474 college students and 234 educators from Bulacan State University (BulSU) who were 18 years or older. Data collection was conducted through face-to-face interaction and Google Forms for educators who requested it. Additionally, five participants were purposely selected for interviews, with students selected from the supreme student government or local student council, and educators must have offices under the Office of the Vice President for Academic Affairs.

2.3 Research Instruments

The researchers modified validated questionnaires from previous studies, obtaining permission from the authors. These questions assessed knowledge, Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Behavioral Intention, and GenAI Acceptance at Bulacan State University (BulSU). The initial 67-item questionnaire was refined to 59 items through face validity and pilot testing (see Appendix A). A 10-point Likert scale was used to indicate their agreement or disagreement with each question, a method shown to have good reliability compared to scales with fewer points (Abdul Malik, Mustapha, Mohamad Sobri, Abd Razak, Mohd Zaidi, Shukri, & Zalimie Sham, 2021). The researchers crafted four open-ended questions, validated by a psychometrician, to collect insights and recommendations on GenAI's university use (see Appendix B).

2.4 Statistical Treatment

The researchers began data processing by cleaning the data, excluding those respondents with missing data. Negative items were re-encoded by reversing their numerical values for consistency. The researchers used various statistical treatments to analyze the data: *Frequency statistics* was used to determine the number of respondents who had used GenAI and to understand the demographic traits of the respondents. *Mean and weighted mean* were computed for each item to determine the overall level of knowledge, agreement, and acceptance, which was interpreted based on predefined intervals (see Table 1). *Standard deviation* was used to measure the spread of the item's response relative to its mean. Moreover, the *one-sample binomial test* was used to determine if about half of the college students and educators at Bulacan State University had used GenAI.

Table 1 *M*ean Score Interval and its Corresponding Meaning

Mean Score Interval	Level of Knowledge	Level of Agreement	Level of Acceptance
1.00 – 2.80	Not at all Knowledgeable	Strongly Disagree	Poorly Acceptable
2.81 – 4.60	Slightly Knowledgeable	Disagree	Fairly Acceptable
4.61 – 6.40	Somewhat Knowledgeable	Neutral	Acceptable
6.41 – 8.20	Moderately Knowledgeable	Agree	Moderately Acceptable
8.21 – 10.00	Extremely Knowledgeable	Strongly Agree	Highly Acceptable

Note. Modified from the studies of Casinillo and Tavera (2021); Bentouhami, and Weyler (2023); and Salac (2018).

Furthermore, the researchers used *Covariance-Based Structural Equation Modeling (CB-SEM)* to analyze the direct, indirect, and total effects among variables in the study and assess the model's validity. CB-SEM is used to confirm or reject hypotheses by evaluating how well a proposed theoretical model can replicate the covariance matrix observed in the sample dataset (Hair, Hult, Ringle, Sarstedt, Danks, & Ray, 2021). The researchers had a sufficient sample size, meeting the CB-SEM requirement of 150-500 participants (Bentler & Chou, 1987). This sample size also supports the normality assumption, as larger sample sizes tend to produce averages that closely resemble a normal distribution, as indicated by the Central Limit Theorem (Mendenhall, Scheaffer, & Wackerly, 2008; Mondiana, Pramoedyo, & Sumarminingsih, 2018).

Table 2 Summary of Confirmatory Factor Analysis Assessment

Name of Assessment		Remark	Requirement	Relevant Literature
Unidimensionality		Achieved	All factor loading is greater than .3	(Hair, Anderson, Tatham, & Black, 1995; Bartlett, Kotrlik, & Higgins, 2001)
Validity	Construct Validity	Achieved	Assessment of Fitness: Absolute Fit Indexes Comparative Fit Parsimony - Adjusted Fit Indexes	(MacCallum, Browne, & Sugawara, 1996; Hu & Bentler, 1999; Byrne, 2001; Jaccard & Wan, 1996; Browne and Cudeck, 1993; Jöreskog & Sörbom, 1986; Tanaka and Huba, 1985; Bentler, 1992; Bollen 1989; Bentler and Bonett, 1980)
	Convergent Validity	Achieved	All Average Variance Extracted values is > .5; else composite reliability must be > .6	(Cheung, Cooper-Thomas, Lau, & Wang, 2023; Fornell & Larcker, 1981)

	Discriminant Validity	Achieved	All HTMT ratios < .85 Six - factor model indicating that the six latent variables are distinctively different	(Henseler, Ringle, & Sarstejdt 2014)
Reliability	Cronbach's Alpha Composite Reliability	Achieved	All values of Cronbach's Alpha and Composite reliability are greater than .6	(Fornell & Larcker, 1981)
No Multicollinearity	Tolerance Level Variance Inflation Factor (VIF)	Achieved	All tolerance level is above .20 All VIF must be below 10	(Menard, 1995; O'Brien, 2007)

In addition, the researchers achieved the assumption of model fit index under construct validity, which indicates the usability of the model drawn from the sample to the population (Kumar & Upadhaya, 2017) (see Table 2). Confirmatory factor analysis (CFA) was used to validate the modified model based on the Unified Theory of Acceptance and Use of Technology (UTAUT). CFA was used to retest the validity measures and measurement model identified in theorized frameworks by applying the instrument to a new sample (O'Rourke & Hatcher, 2013).

Lastly, the researchers used *the Welch t-test* to determine whether a significant difference exists between the acceptance level of college students and educators on GenAI. According to Sakai (2016), the Welch t-test is appropriate when the variance of two distinct groups is different from each other or when the sample sizes of the two groups are different. The validity of accepting these assumptions was justified, as college students and educators belonged to separate groups with distinct sample sizes.

3. Results and Discussions

In this section, the results and findings of the data were explored. The researchers methodically presented tables, figures, and their interpretations to fully comprehend the study's findings. All the information presented in this section directly addresses the research questions posed at the beginning. Through careful examination and clear presentation of the data, the researchers ensure that the findings provide valuable insights into the topics under investigation.

3.1 Proportion of College Students and Educators who have used Generative Artificial Intelligence (GenAI)

Table 3 Proportion of College Students and Educators who have used GenAI

Demographic Profile	**Proportion of who have used GenAI (%)**			
	College Students		Educators	
	Yes	No	Yes	No
	85.84	14.16	76.11	23.89
Sex				
Male	84.32	15.68	78.43	21.57
Female	86.89	13.11	75.00	25.00
Age				
18 – 24	85.68	14.32	100.00	0.00
25 - 34	100.00	0.00	82.05	17.95
35 - 44	-	-	84.13	15.87
45 - 54	-	-	54.55	45.45
55 - 64	-	-	33.33	66.67
College Affiliation				
COE	98.55	1.45	75.00	25.00
CHTM	97.22	2.78	50.00	50.00
CCJE	96.43	3.57	75.00	25.00
CSSP	92.31	7.69	74.07	25.93
CAFA	86.96	13.03	75.00	25.00
CICT	86.05	13.95	85.19	14.81
CBA	85.71	14.29	50.00	50.00
COED	84.44	15.56	76.47	23.53
CON	80.00	20.00	80.00	20.00
CSER	75.00	25.00	50.00	50.00
CAL	69.23	30.77	83.33	16.67
CS	65.71	34.29	88.89	11.11

Note. n = 678, **COE** - College of Engineering, **CHTM** - College of Hospitality and Tourism Management, **CCJE** - College of Criminal Justice and Education, **CSSP** - College of Social Science and Philosophy, CAFA - College of Architecture and Fine Arts, CICT - College of Information and Communications Technology, **CBA** - College of Business Administration, **COED** - College of Education, **CON** - College of Nursing, **CIT** - College of Industrial Technology, **CSER** - College of Sports, Exercise, and Recreation, **CAL** - College of Arts and Letters, and **CS** - College of Science

The gathered valid sample consists of 452 college students and 226 educators. The proportion of college students who have used GenAI is approximately 6 out of 7, while for educators, approximately 3 out of 4 utilized the said tool. Among these GenAI users, 84.32% of college students and 78.43% of educators are male, while 86.89% of college students and 75.00% of educators are female.

Regarding age distribution, the data is divided into five age groups. Among college students, 85.68% are in the 18-24 age group, and all educators in this group have used GenAI tools. For the 25-34 age group, all college students and 82.05% of educators have used GenAI. Among educators aged 35-44, 84.13% have used GenAI, while for those aged 45-54, the usage rate is 54.55%. Finally, 33.33% of educators aged 55-64 have used GenAI. This trend suggests that GenAI usage declines as the age of the educators increases.

In terms of college affiliation, the College of Engineering (COE), College of Hospitality and Tourism Management (CHTM), and College of Criminal Justice and Education (CCJE) reported the highest GenAI usage rates among students at 98.55%, 97.22%, and 96.43%, respectively. Among educators, the College of Science (CS), College of Information and Communications Technology (CICT), and College of Arts and Letters reported the highest usage rates at 88.89%, 85.19%, and 83.33%, respectively.

Several administrative councils, local student councils, and student government members support using GenAI tools in higher education institutions based on the interviews conducted by the researchers. They emphasize the need for responsible use, noting the lack of existing policies and guidelines. They also stress the importance of addressing ethical issues and adhering to standards set by faculty members.

Parameter Estimates and Confidence Intervals of GenAI Usage

The researchers investigated whether more than 50% of college students and educators at Bulacan State University (BulSU) have utilized Generative Artificial Intelligence (GenAI). This examination aims to measure the level of adoption of GenAI within the BulSU community and its potential impact on educational settings.

Table 4 Parameter Estimates and Confidence Intervals of GenAI Usage

Respondent	Estimate	95% Confidence Interval		p - value
		Lower	Upper	
College Students	.858	.823	.889	.000
Educators	.761	.700	.815	.000

researchers used a one-sample binomial test for both college students and educators to show significant GenAI usage, with prevalence rates exceeding 50% in both groups. Hence, $H_{o(1)}$ was rejected. These findings contradict the study of Shaw et al. (2023), which reveals that approximately 50% of the students have utilized GenAI, and only 25% of the educators are employing this technology in their academic experience. It highlights the continuous innovation and utilization of the educational community about the possible use of GenAI in their institutions. On the other hand, the confidence intervals provide additional context, indicating estimated precision and highlighting result robustness (see Table 4).

3.2 Level of Knowledge among College Students and Educators about the Limitations of GenAI

The researchers investigated the general knowledge of both college students and educators regarding the limitations of GenAI tools. The level of knowledge solely serves as a guiding tool for the researchers to understand how the respondents perceive the limitations of GenAI. The findings of the previous study of Chan and Hu (2023) indicate that the participants exhibited a strong understanding of GenAI tools and expressed a preference for their integration into academic settings. However, concerns about their use revealed only a slight approval among respondents. In the present study, findings revealed that college students and educators at Bulacan State University-Main Campus demonstrated a moderate understanding of the limitations of GenAI tools.

Table 5 Level of Knowledge of the College Students and Educators

I understand GenAI has/can/may	College Students			Educators		
	Mean	SD	VI	Mean	SD	VI
Limitation in their ability to handle complex tasks.	8.45	1.868	EK	8.11	1.921	MK
Generate output that is factually inaccurate.	7.89	2.064	MK	8.10	1.921	MK
Generate output that is out of context or inappropriate.	7.53	2.384	MK	7.81	2.150	MK
Exhibit biases and unfairness in their output.	7.59	2.119	MK	8.12	1.994	MK
Rely too heavily on statistics, which can limit their usefulness in certain contexts.	7.79	2.083	MK	7.67	1.973	MK
Limited emotional intelligence and empathy, which can lead to output that is insensitive or inappropriate.	8.04	2.245	MK	8.15	2.049	MK
WEIGHTED MEAN	**7.88**	**MK**		**7.99**	**MK**	

Note. **SD** - Standard Deviation, **VI** - Verbal Interpretation, **EK** - Extremely Knowledgeable, and **MK** - Moderately Knowledgeable.

The mean values for the level of knowledge among students range from 7.53 to 8.45, while the mean values among the educators range from 7.67 to 8.15 (see Table 5). Most of the college students were extremely knowledgeable to understand that the ability of GenAI in handling complex tasks has limitations while the educators are moderately knowledgeable to the same statement. Moreover, college students and empathy, which can lead to insensitive and inappropriate output.

Furthermore, college students and educators were moderately knowledgeable that GenAIs can generate output that is factually inaccurate, out of context or inappropriate, exhibit biases and unfairness, and rely heavily on statistics that limit their usefulness in certain contexts. The overall mean values were 7.88 for college students and 7.99 for educators, both corresponding to a verbal interpretation of moderately knowledgeable. It suggests that respondents generally have a moderate knowledge of the limitations of GenAIs to handle complex tasks, to be factually inaccurate, out of context or inappropriate, could exhibit biases and unfairness, rely too heavily on statistics that limits its usefulness, and have limited emotional intelligence and empathy in generating outputs.

Moreover, the standard deviation of the college students for each item ranged from 1.87 to 2.38, and 1.92 to 2.15 for the educators. These values indicate a high level of dispersion, meaning that the responses are more spread out from the mean value, indicating that there is more variability among the responses, suggesting that perceptions regarding the level of knowledge among respondents vary to a greater extent.

3.3 College Students' and Educators' Perceptions on GenAI

In this study, researchers analyzed college students' and educators' perceptions of GenAI, focusing on factors like performance expectancy (PE), effort expectancy (EE), social influence (SI), facilitating condition (FC), and behavioral intention (BI). Descriptive analysis reveals how these factors affect GenAI acceptance. Understanding these perceptions, valuable insights on the effectiveness and challenges of integrating GenAI in academia help researchers better understand what motivates people to use these GenAI tools in higher education institutions.

Table 6 Perceptions of College Students and Educators

Performance Expectancy Criteria	**College Students**			**Educators**		
	Mean	SD	VI	Mean	SD	VI
Incorporating GenAI in my academics would simplify my academic tasks.	7.29	2.069	MA	7.27	1.937	MA
GenAI serves as a valuable tool for addressing my questions.	6.99	2.033	MA	7.08	1.971	MA
Incorporating GenAI would lead me to more efficient task completion.	6.90	2.038	MA	7.11	1.939	MA
The implementation of GenAI would increase my productivity.	5.89	2.408	A	6.60	2.255	MA
GenAI enhances my learning capabilities.	6.46	2.252	MA	6.69	2.156	MA
I find GenAI more useful than other sources of information that I have used in the past.	6.15	2.468	A	6.34	2.274	A
WEIGHTED MEAN	**6.61**	**MA**		**6.85**		**MA**
Effort Expectancy Criteria						
GenAI seems to be user – friendly.	7.78	2.016	MA	7.51	1.936	MA
My interaction with GenAI is comprehensible.	7.02	1.976	MA	7.09	1.929	MA
I find learning to use GenAI would be manageable.	7.11	2.034	MA	7.23	1.980	MA
Using GenAI makes it easy for me to generate and acquire knowledge.	7.21	2.123	MA	7.07	2.093	MA
WEIGHTED MEAN	**7.28**	**MA**		**7.23**	**MA**	
Social Influence Criteria						
My colleagues encouraged me to use GenAI.	5.58	2.708	A	5.90	2.454	A
People around me think I should use GenAI.	5.37	2.490	A	6.09	2.278	A
People who are important to me think that I should use GenAI.	5.21	2.499	A	6.04	2.509	A
I will be inclined to use the GenAI if my family members adopt it.	5.05	2.477	A	5.94	2.488	A
WEIGHTED MEAN	**5.30**	**A**		**5.99**	**A**	
Facilitating Conditions Criteria						
I can have an online help while using GenAI.	6.47	2.481	MA	6.99	2.294	MA
I think that using GenAI fits well with the way I like to learn.	5.60	2.509	A	6.26	2.458	A
I think a specific person (or group) is available for assistance with the use of GenAI.	5.63	2.602	A	6.05	2.598	A
If I have problems using GenAI, I could solve them very quickly.	6.02	2.545	A	6.27	2.344	A
WEIGHTED MEAN	**5.93**	**A**		**6.39**	**A**	

Note. **SD** – Standard Deviation, **VI** – Verbal Interpretation, **MA** – Moderately Acceptable, and **A** – Acceptable.

Performance expectancy indicates that college students and educators perceive GenAI technologies to be moderately acceptable as a practical tool used for accomplishing a particular task, including through the lens of education (see Table 6). It includes moderate acceptance of GenAI as a tool that is utilized for enhancing productivity, efficiency, and learning capabilities. Similarly, Effort Expectancy shows that they perceived GenAI to be moderately acceptable as a practical tool that requires little to no effort when utilized.

On the other hand, Social Influence verbal interpretation is acceptable for both students and educators in all statements under these stated factors (see Table 6). This implies that it is acceptable for the respondents that their respective decisions to adopt and use new GenAI are influenced by the opinions, encouragement, acceptance, and views of their families, colleagues, and other people. Also, respondents perceive Facilitating Conditions as acceptable suggesting that the institution or university can support, help, and assist the utilization of GenAI technologies by providing necessary resources and a conducive environment (see Table 6).

Table 7 Perception of the College Students and Educators on Behavioral Intention

Behavioral Intention Criteria	College Students			Educators		
	Mean	SD	VI	Mean	SD	VI
Utilizing GenAI enhances my learning experience.	6.42	2.470	A	6.62	2.262	A
I have used GenAI in the past for my academic queries.	7.05	2.296	A	6.81	2.367	A
I intend to expand my use of GenAI in academic duties.	5.66	2.542	N	5.95	2.544	N
Continuing to use GenAI for academic purposes remains part of my plan.	5.54	2.523	N	6.12	2.481	N
WEIGHTED MEAN	**6.17**		**N**	**6.38**		**N**

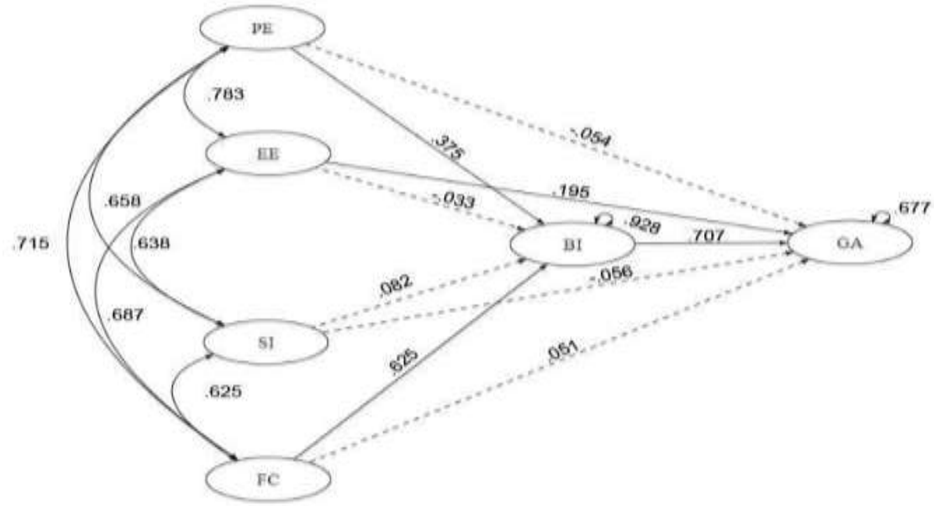
Note. **SD** - Standard Deviation, **VI** - Verbal Interpretation, **A** - Agree, and **N** - Neutral.

In addition, both groups gave neutral responses regarding the level of agreement regarding Behavioral Intention (BI) based on the overall computed mean for this factor (see Table 7). It shows uncertainty in the perception of the respondents regarding their intention to use GenAI tools. Lastly, the researchers found that the respondents, which consist of both college students and educators, have the same verbal interpretation in all statements of BI.

3.4 Structural Model Diagram of the Study

The researchers investigated the direct, indirect, and total effects of performance expectancy, effort expectancy, social influence, and facilitating conditions on the behavioral intention and acceptance of college students on Generative Artificial Intelligence (GenAI). Examining those effects helped them to recommend actionable insights for the usage of GenAI in higher education institutions.

Figure 1 Structural Model Diagram



Note. **Solid line** - Significant, **Broken line** - Insignificant, **PE**- Performance Expectancy, **EE** - Effort Expectancy, **SI** - Social Influence, **FC** - Facilitating Conditions, **BI** - Behavioral Intention, and **GA** - GenAI Acceptance.

Table 8 Direct Effects Estimates

Hypothesized Direct Effect	Estimates	Standard Error	p-value	Result
$H_{o(2a)}$: PE → GA	-.054	.205	.739	Not Rejected
$H_{o(2b)}$: EE → GA	.195*	.097	< .05	Rejected
$H_{o(2c)}$: SI → GA	-.056	.057	.408	Not Rejected
$H_{o(2d)}$: FC → GA	.051	.596	.842	Not Rejected
$H_{o(2e)}$: BI → GA	.707*	.310	< .05	Rejected
$H_{o(3a)}$: PE → BI	.375***	.122	< .01	Rejected
$H_{o(3b)}$: EE → BI	-.033	.101	.652	Not Rejected
$H_{o(3c)}$: SI → BI	.082	.057	.157	Not Rejected
$H_{o(3d)}$: FC → BI	.625***	.388	< .01	Rejected

Note. **PE -** Performance Expectancy, **EE -** Effort Expectancy, **SI -** Social Influence, **FC -** Facilitating Conditions, **BI -** Behavioral Intention, and **GA -** GenAI Acceptance. Model fit: **GFI** = .865, **CFI =** .940, **NFI** = .897, **TLI** = .930, **SRMR** = .0449, **RMSEA** = .057, and **chisq/df** = 2.254.
*** significant at the .01 level. * significant at the .05 level.

From the results of the analysis, it is evident that both PE and FC exhibit significant positive direct effects on college students' BI to use GenAI ($H_{o(3a)}$ and $H_{o(3d)}$ were rejected). It emphasizes the importance of usefulness and adequate support for the technology. Integrating GenAI tools in higher education institutions ensures the acceptance of college students with its usability and supportive resources such as seminars, training, orientation, and well-established guidelines for the responsible use of these tools. In contrast, EE and SI do not significantly directly affect the intention to use GenAI of college students ($H_{o(3b)}$ and $H_{o(3c)}$ were not rejected).
The significant effect of PE and FC on BI emphasize the importance of usefulness and adequate support for the technology. Integrating GenAI tools in higher education institutions ensures the acceptance of college students with its usability and supportive resources such as seminars, training, orientation, and well-established guidelines for the responsible use of these tools.
On the other hand, there is a significantly direct effect of EE on the acceptance of GenAI ($H_{o(2b)}$ was rejected) underscores the critical role of simplicity and ease of use towards acceptance of GenAI. This finding suggests that when college students perceive GenAI as user-friendly, they are more likely to accept the technology. Furthermore, the other three constructs, which are PE, SI, and FC do not directly affect the acceptance of GenAI among college students in the context of this study ($H_{o(2a)}$, $H_{o(2c)}$, and $H_{o(2d)}$ were not all rejected).
The study's findings show the significant effect of EE in the acceptance of GenAI highlights the importance of user-friendliness, indicating that while ease of use might not influence initial intent to use, it is crucial for sustained acceptance and use. This finding suggests that designing intuitive and accessible GenAI applications could enhance student engagement and long-term adoption.
Moreover, the BI of college students on their GenAI has a positive and significant effect on their acceptance ($H_{o(2e)}$ was rejected). It demonstrates that when college students are willing to use GenAI, it strongly affects their feelings towards it, emphasizing how their interest affects acceptance levels. It underscores that the strong effect between BI and acceptance of GenAI illustrates that enhancing students' intentions to use this technology could lead to higher acceptance levels. This relationship supports the development of educational strategies that foster positive attitudes towards GenAI, potentially leading to more widespread acceptance and integration into academic pursuits. These findings not only guide the deployment of educational technology but also point to new directions for research in understanding and enhancing technology acceptance among students.

Table 9 Indirect Effects Estimates

Hypothesized Mediation Effect	**Estimates**	**Standard Error**	**p-value**	**Result**
$H_{o(4a)}$: PE → BI → GA	.265	.573	.104	Not Rejected
$H_{o(4b)}$: EE → BI → GA	-.023	.183	.772	Not Rejected
$H_{o(4c)}$: SI → BI → GA	.058	.122	.359	Not Rejected
$H_{o(4d)}$: FC → BI → GA	.442	1.950	.103	Not Rejected

Note. **PE** - Performance Expectancy, **EE** - Effort Expectancy, **SI** - Social Influence, **FC** - Facilitating Conditions, **BI** - Behavioral Intention, and **GA** - GenAI Acceptance. **Number of bootstrap samples** = 5000 and **PC confidence level** = 95. Model fit: **GFI** = .865, **CFI =** .940, **NFI** = .897, **TLI** = .930, **SRMR** = .0449, **RMSEA** = .057, and **chisq/df** = 2.254.

The study's findings suggest that factors PE, EE, SI, and FC may affect individuals' intentions to use GenAI technology within academic settings. However, when it comes to the actual acceptance of GenAI, these factors do not seem to exert a significant indirect effect on individuals' behavioral intentions ($H_{o(4)}$ was not rejected) (see Table 9). The study's findings suggest that factors PE, EE, SI, and FC may affect individuals' intentions to use GenAI technology within academic settings.

However, when it comes to the actual acceptance of GenAI, these factors do not exert a significant indirect effect on individuals' behavioral intentions. It means that while college students and educators may recognize the potential benefits of GenAI, such as improving their performance, making their academic tasks easier, and such, their intention to use it does not necessarily translate into actual acceptance and utilization.

Table 10 Total Effects Estimates

Hypothesized Total Effect	Estimates	Standard Error	p-value	Result
$H_{o(5a)}$: PE → (BI) → GA	.211	.110	.065	Not Rejected
$H_{o(5b)}$: EE → (BI) → GA	.172	.096	.076	Not Rejected
$H_{o(5c)}$: SI → (BI) → GA	.002	.077	.967	Not Rejected
$H_{o(5d)}$: FC → (BI) → GA	.493***	.099	< .01	Rejected

Note. **PE** - Performance Expectancy, **EE** - Effort Expectancy, **SI** - Social Influence, **FC** - Facilitating Conditions, **BI** - Behavioral Intention, and **GA** - GenAI Acceptance. **Number of bootstrap samples** = 5000 and **PC confidence level** = 95. Model fit: **GFI** = .865, **CFI** = .940 , **NFI** = .897, **TLI** = .930, **SRMR** = .0449, **RMSEA** = .057 , and **chisq/df** = 2.254
*** significant at the .01 level.

The study found that performance expectancy, effort expectancy, and social Influence have no significant total effect on the way the students intend to accept GenAI ($H_{o(5a)}$, $H_{o(5b)}$, and $H_{o(5c)}$ were not rejected). However, Facilitating Conditions (FC) had a significant and positive total effect on their acceptance ($H_{o(5d)}$ was not rejected). This finding underscores the importance of supportive resources and conditions in affecting the college students' of GenAI technologies. FC plays a crucial role in shaping students' attitudes and intentions toward GenAI, highlighting the significance of providing appropriate resources and supportive environments to promote technology acceptance in educational settings.

Table 11 Squared Multiple Correlations

Construct	R-Square
Behavioral Intention	.928
GenAI Acceptance	.677

The high variance values for Behavioral Intention (BI) and GenAI Acceptance (GA) indicate the strong influence of Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC) on these constructs (see Table 10). These findings enhance the understanding of the effect within the model and emphasize the importance of these factors in predicting BI and GA.

3.5 Difference on the Acceptance of GenAI based on their Academic Role

The researchers investigated the acceptance of college students and educators to use Generative Artificial Intelligence (GenAI) or similar AI tools in their academic experience or environment, or simply the GenAI acceptance. The proponents tested whether there was a significant difference in their perception regarding GenAI acceptance.

Table 12 T - test table of GenAI Acceptance based on their Academic Role

I can accept GenAI based on its	College Students Mean	VI	Educators Mean	VI	Mean Difference	p-value
Value	6.63	MA	6.74	MA	-.11	.580
Accuracy	6.52	MA	6.55	MA	-.03	.889
Benefit	7.37	MA	7.35	MA	.02	.943
Accessibility	7.75	MA	7.60	MA	.15	.420
Decision-making capabilities	6.09	A	6.34	A	-.25	.231
Transparency and explainability	6.83	MA	6.78	MA	.05	.833
Privacy and data security	5.96	A	6.08	A	-.12	.626
Previous experience	6.92	MA	6.90	MA	.02	.937
Social and ethical implications	6.14	A	6.30	A	-.16	.456

Note. **VI** - Verbal Interpretation, **MA** - Moderately Acceptable, and **A** - Acceptable.

To expand further, the researchers measured the level of GenAI acceptance and explored it using descriptive analysis. There are two distinct groups, which consist of both college students and educators. Both college students and educators have the highest acceptance based on GenAI's accessibility, while its privacy and data security have the lowest acceptance (see Table 12).
For college students, the average value for each item ranges from 5.96 to 7.75. The college students accepted the GenAI based on its decision-making capabilities, privacy and data security, and social and ethical

implications. However, the students responded that they have a higher level of agreement and acceptance on six particular statements with average values ranging from 6.52 to 7.75. They shared a moderate level of acceptance pertaining to GenAI's value, accuracy, benefit, accessibility, transparency and explainability, and previous experience.
For educators, the mean values for the statements above range from 6.08 to 7.35. They accepted GenAI based on its decision-making capabilities, privacy and data security, and social and ethical implications. The same with students, the educators also shared higher levels of agreement acceptance on statements related to GenAI's value, GenAI's value, accuracy, benefit, accessibility, transparency and explainability, and previous experience.
Overall, all items presented in the table have the same verbal interpretation across both college students and educators. The level of acceptance of the college students and educators was moderately acceptable. Furthermore, the researchers utilized Welch's t-test to test the difference in the mean for GenAI acceptance between college students and educators. Each aspect or item of GenAI acceptance was tested, particularly in terms of GenAI's value, accuracy, benefit, accessibility, decision-making capabilities, transparency and explainability, privacy and data security, previous experience, and social and ethical implications.
All computed p-values range fell in the range of 0.231 to 0.943, with each single value being greater than the conventional alpha value of 0.05. Hence, the researchers do not reject the null hypothesis (Ho(6)) due to the lack of statistical evidence. It implies that there is no significant difference in the level of GenAI acceptance between college students and educators regarding GenAI's value, accuracy, benefit, accessibility, decision-making capabilities, transparency and explainability, privacy and data security, previous experience, and social and ethical implications. In conclusion, the GenAI acceptance in both students and educators is statistically the same as related to the initial results where both groups have the same level of acceptance, which is moderately acceptable.

3.6 Suggested Actionable Insights for the Usage of GenAI in HEIs

As of the 2nd semester of the school year 2023-2024, the Bulacan State University (BulSU) has not yet imposed an official policy regarding Generative Artificial Intelligence (GenAI). The researchers suggest that faculty members set their rules or regulations inside their respective learning environments as an alternative and pre-emptive measure for GenAI utilization. It can be in the form of regulations based on the other universities, such as allowing or disallowing the usage of GenAI supervised by the educator (Stanford University, 2023), or tools will be treated as another form of resources that shall be cited appropriately (Chenjp, 2023). This approach will temporarily help educators regarding the utilization of GenAI tools, given that the study's findings suggest that students are more likely to accept GenAI if they believe that the institution supports its use and if these GenAI tools are easy to use.
On the other hand, the university administrative council plays a vital role by providing support mechanisms for both college students and educators regarding the utilization of GenAI tools based on the result that facilitating conditions have a total effect on GenAI acceptance as a reference with the University of the Philippines Open University's (UPOU) Memorandum CMDPB 2024-001. Moreover, one of the BulSU administrative councils, together with several student councils, suggested that the university should be proactive in confronting issues arising from the use of GenAI tools. It can be in the form of professional training, seminars, AI literacy workshops, official policies, sanctions, and guidelines to mitigate the responsible use of the said technology. They can also develop awareness regarding ethical usage, data privacy, compliance, and algorithm transparency, which are relevant to future policy. With these actionable insights, the student's intent to use GenAI tools can be directly affected by their perception that it can be a practical tool useful in higher education while being a responsible user.
Furthermore, the establishment of a dedicated support team in the future that will oversee the implementation of the policy, partnership, and collaboration with experts in the field would be beneficial once the official policies and guidelines are implemented, as stated by one of the administrators. It will significantly help educators be aware and knowledgeable of current advancements while informing students on ways to use GenAI responsibly while preserving academic integrity and excellence.
Lastly, the university may explore different ways, methods, strategies, and new approaches to how faculty members teach and assess student learning while considering the new era of technology called AI is already here, and further usage of it is nearly possible in the future. As stated by one of the student government members, it can be done by integrating a particular software to set certain restrictions for the students while being facilitated by the faculty. On the other hand, another administrator advised embracing a new approach to assessment called Outcome-Based Education (OBE) for the students, given the advancement of technology. They stated that this would give more emphasis on the student's skills, understanding, and competency while being able to think critically rather than just copying and pasting ideas from other sources, including AI. A student council member also expressed that a new approach would help educators develop a new way to measure the students' capacities while ensuring the authenticity of the students' outputs.

Conclusion

The study underscores a remarkable uptake of Generative Artificial Intelligence (GenAI) among college students, with 6 out of 7 having utilized it and 3 out of 4 educators already using the said tool. It indicates its visible utilization in academic endeavors within the Bulacan State University (BulSU) community. Furthermore, effort expectancy emerged as a positive and significant construct affecting the acceptance of college students on GenAI. The acceptance of GenAI for college students directly affects them when they find the tool easy to use. Moreover, behavioral intention demonstrated a significant and positive effect on GenAI acceptance suggesting that enhancing college students' intentions to use this technology could lead to higher acceptance levels. Notably, performance expectancy significantly affects behavioral intention, indicating that when GenAI simplifies academic tasks, it becomes a preferred resource for productivity and learning enhancement.

Additionally, facilitating conditions affect behavioral intention positively, indicating the importance of institutional support for college students to intend to use GenAI tools. At the same time, only facilitating conditions have a significant total effect on their acceptance of GenAI. It emphasizes the critical role of institutional resources and support in fostering acceptance among college students. Importantly, the study reveals no significant difference in GenAI acceptance between college students and educators, indicating a uniform level of acceptance across both groups. It suggests a promising avenue for collaborative exploration and implementation of GenAI in educational settings, fostering a collaboration relationship between college students and educators in leveraging its benefits.

References

1. Abdul Malik, M. A., Mustapha, M. F., Mohamad Sobri, N., Abd Razak, N. F., Mohd Zaidi, M. N., Shukri, A. A., & Zalimie Sham, M. A. L. (2021). Optimal Reliability and Validity of Measurement Model in Confirmatory Factor Analysis: Different Likert Point Scale Experiment. Journal of Contemporary Issues and Thought, 11(1), 105–112. https://doi.org/10.37134/jcit.vol11.9.2021
2. Bartlett, J., Kotrlik, J., & Higgins, C. (2001). Organizational research: Determining appropriate sample size in survey research appropriate sample size in survey research. Information technology, learning, and performance journal, 19(1), 43.
3. Bentler, P. M. (1992). On the fit of models to covariances and methodology to the Bulletin. Psychological Bulletin, 112(3), 400–404. https://doi.org/10.1037/0033-2909.112.3.400
4. Bentler, P. M., & Bonett, D. G. (1980). Significance tests and goodness of fit in the analysis of covariance structures. Psychological Bulletin, 88(3), 588–606. https://doi.org/10.1037/0033-2909.88.3.588
5. Bentler, P. M., & Chou, C. P. (1987). Practical issues in structural modeling. Sociological Methods & Research, 16(1), 78–117. https://doi.org/10.1177/0049124187016001004
6. Bollen, K. A. (1989). Structural Equations with Latent Variables. John Wiley & Sons, Inc. https://doi.org/10.1002/9781118619179
7. Browne, M., & Cudeck, R. (1993). Alternative ways of assessing model fit. In K. A. Bollen & J. S. Long (Eds.), Testing structural equation models (pp. 136–162). Beverly Hills, CA: Sage.
8. Byrne, B. (2001). Structural equation modeling with Amos: Basic concepts, applications, and programming. Mahwah, NJ: Lawrence Erlbaum Associates.
9. Casinillo, L. F., & Tavera, G. F. (2021). ON THE DARK SIDE OF LEARNING CALCULUS: EVIDENCE FROM AGRIBUSINESS STUDENTS. IJIET (International Journal of Indonesian Education and Teaching), 5(1), 52–60. https://doi.org/10.24071/ijiet.v5i1.2825
10. Chan, C., & Hu, W. (2023). Students' Voices on Generative AI: Perceptions, Benefits, and Challenges in Higher Education. International Journal of Educational Technology in Higher Education, 20(43). https://doi.org/10.48550/arxiv.2305.00290
11. Chenjp, S. (2023, April 18). Honor Council limits use of ChatGPT. The Rice Thresher. https://www.ricethresher.org/article/2023/04/honor-council-limits-use-of-chatgpt
12. Cheung, G., Cooper-Thomas, H. D., Lau, R. S., & Wang, L. C. (2023). Reporting reliability, convergent and discriminant validity with structural equation modeling: A review and best-practice recommendations. Asia Pacific Journal of Management. https://doi.org/10.1007/s10490-023-09871-y
13. Coffey, L. (2023, October 31). Students Outrunning Faculty in AI Use. Inside Higher Ed. https://www.insidehighered.com/news/tech-innovation/artificial-intelligence/2023/10/31/most-students-outrunning-faculty-ai-use
14. Cotton, D. R. E., Cotton, P. A., & Shipway, J. R. (2023). Chatting and cheating: Ensuring academic integrity in the era of ChatGPT. Innovations in Education and Teaching International, 1–12. https://doi.org/10.1080/14703297.2023.2190148
15. Farrelly, T., & Baker, N. (2023). Generative Artificial Intelligence: Implications and Considerations for Higher Education Practice. Education Sciences, 13(11), 1109. https://doi.org/10.3390/educsci13111109
16. Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. Journal of Marketing Research, 18(1), 39–50. https://doi.org/10.1177/002224378101800104

17. Gerlich, M. (2023). Perceptions and Acceptance of Artificial Intelligence: A Multi-Dimensional Study. Social Sciences, 12(9), 502. https://doi.org/10.3390/socsci12090502
18. Haglund, J. (2023). Students Acceptance and Use of ChatGPT in Academic Settings (pp. 6, 7). Uppsala Universitet.
19. Hair, J., Anderson, R., Tatham, R., & Black, W. (1995). Multivariate data analysis (4th ed.). Upper Saddle River, NJ: Prentice Hall.
20. Hair, J., Hult, G., Ringle, C., Sarstedt, M., Danks, N., & Ray, S. (2021). An introduction to structural equation modeling. In Classroom companion: business (pp. 1–29). https://doi.org/10.1007/978-3-030-80519-7_1
21. Henseler, J., Ringle, C. M., & Sarstedt, M. (2014). A new criterion for assessing discriminant validity in variance-based structural equation modeling. Journal of the Academy of Marketing Science, 43(1), 115–135. https://doi.org/10.1007/s11747-014-0403-8
22. Hu, L., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. Structural Equation Modeling: A Multidisciplinary Journal, 6(1), 1–55. https://doi.org/10.1080/10705519909540118
23. Jaccard, J., & Wan, C. (1996). LISREL approaches to interaction effects in multiple regression. SAGE Publications, Inc. https://doi.org/10.4135/9781412984782
24. Johnson, A. (2023). ChatGPT In Schools: Here's Where It's Banned—And How It Could Potentially Help Students. Forbes. https://www.forbes.com/sites/ariannajohnson/2023/01/18/chatgpt-in-schools-heres-where-its-banned-and-how-it-could-potentially-help-students/
25. Jöreskog, K. G., & Sörbom, D. (1986). LISREL VI: Analysis of Linear Structural Relationships by Maximum Likelihood, Instrumental Variables, and Least Squares Methods. Scientific Software.
26. Klainin-Yobas, P., He, H., & Lau, Y. (2015). Physical fitness, health behaviour and health among nursing students: A descriptive correlational study. Nurse Education Today, 35(12), 1199–1205. https://doi.org/10.1016/j.nedt.2015.06.014
27. Kumar, S., & Upadhaya, G. (2017). STRUCTURE EQUATION MODELING BASIC ASSUMPTIONS AND CONCEPTS: A NOVICES GUIDE. International Journal of Quantitative and Qualitative Research Methods, 5(4), 10–16.
28. Lim, W. M., Gunasekara, A., Pallant, J. L., Pallant, J. I., & Pechenkina, E. (2023). Generative AI and the Future of education: Ragnarök or reformation? a Paradoxical Perspective from Management Educators. The International Journal of Management Education, 21(2), 100790. https://doi.org/10.1016/j.ijme.2023.100790
29. MacCallum, R. C., Browne, M. W., & Sugawara, H. M. (1996). Power analysis and determination of sample size for covariance structure modeling. Psychological Methods, 1(2), 130–149. https://doi.org/10.1037/1082-989x.1.2.130
30. Menard S. (1995). Applied logistic regression analysis. Thousand Oaks, CA: Sage.
31. Mendenhall, W., Scheaffer, R. L., & Wackerly, D. D. (2008). Mathematical Statistics With Applications (7th ed.). Thomson Brooks-Cole.
32. Mondiana, Y., Pramoedyo, H., & Sumarminingsih, E. (2018). Structural equation modeling on Likert scale data with transformation by successive interval method and with no transformation. International Journal of Scientific and Research Publications, 8(5). https://doi.org/10.29322/ijsrp.8.5.2018.p7751
33. O'Brien, R. M. (2007). A caution regarding rules of thumb for variance inflation factors. Quality and Quantity, 41(5), 673–690. https://doi.org/10.1007/s11135-006-9018-6
34. O'Rourke, N., & Hatcher, L. (2013). A step-by-step approach to using SAS for factor analysis and structural equation modeling (2nd ed.). SAS Institute Inc.
35. Pinzolits, R. (2023). AI in academia: An overview of selected tools and their areas of application. MAP Education and Humanities, 4(2744-2373), 37–50. https://doi.org/10.53880/2744-2373.2023.4.37
36. Rajendra, P., Kumari, M., Rani, S., Dogra, N., Boadh, R., Kumar, A., & Dahiya, M. (2022). Impact of artificial intelligence on civilization: Future perspectives. Materials Today: Proceedings, 56(2214-7853). https://doi.org/10.1016/j.matpr.2022.01.113
37. Salinas-Navarro, D. E., Vilalta-Perdomo, E., Michel-Villarreal, R., & Montesinos, L. (2024). Using Generative Artificial Intelligence Tools to Explain and Enhance Experiential Learning for Authentic Assessment. Education Sciences, 14(1), 83. https://doi.org/10.3390/educsci14010083
38. Sakai, T. (2016). Two Sample T-tests for IR Evaluation. International Review of Social Psychology, 30(1). https://doi.org/10.1145/2911451.2914684
39. Senechal, J., Ekholm, E., Samaher Aljudaibi, Strawderman, M., & Parthemos, C. (2023). Balancing the Benefits and Risks of AI Large Language Models in K12 Public Schools. VCU Scholars Compass. https://scholarscompass.vcu.edu/merc_pubs/133/
40. Shaw, C., Yuan, L., Brennan, D., Martin, S., Janson, N., Fox, K., & Bryant, G. (2023, October 23). GENERATIVE AI IN HIGHER EDUCATION: FALL 2023 UPDATE OF TIME FOR CLASS STUDY. Tyton Partners. tytonpartners.com/time-for-class-2023/GenAI-Update
41. Shuhaiber, A. (2016). How facilitating conditions impact students' intention to use virtual lectures? An empirical evidence. AICT 2016, 79.

42. Standford University. (2023). Generative AI Policy Guidance | Office of Community Standards. Community standards. stanford.edu. https://communitystandards.stanford.edu/generative-ai-policy-guidance
43. Tanaka, J. S., & Huba, G. J. (1985). A fit index for covariance structure models under arbitrary GLS estimation. British Journal of Mathematical and Statistical Psychology, 38(2), 197–201. https://doi.org/10.1111/j.2044-8317.1985.tb00834.x
44. Tanner, K. (2002). Survey research. In Elsevier eBooks (pp. 89–109). https://doi.org/10.1016/b978-1-876938-42-0.50013-7
45. Teo, T. (2011). Technology Acceptance Research in Education. Technology Acceptance in Education, 1–5. https://doi.org/10.1007/978-94-6091-487-4_1
46. UNESCO. (2023). Generative Artificial Intelligence in education: What are the opportunities and challenges? Unesco.org. https://www.unesco.org/en/articles/generative-artificial-intelligence-education-what-are-opportunities-and-challenges
47. Vaccino-Salvadore, S. (2023). Exploring the Ethical Dimensions of Using ChatGPT in Language Learning and Beyond. Languages, 8(3), 191–191. https://doi.org/10.3390/languages8030191

APPENDIX A

Republic of the Philippines
Bulacan State University
City of Malolos, Bulacan
Tel/Fax (044) 791-0153

COLLEGE OF SCIENCE

The journey to excellence starts here.

Demographic Profile

Name (*optional*): ________________ Academic Role*: ☐ Faculty ☐ Student

Sex*: ☐ Male ☐ Female Age*: ____ College Affiliation*: _______

*I have used GenAI**: ☐ Yes ☐ No

Instruction: Please put your answer in the "*Survey Answer Sheet*" to indicate your rate of agreement with the items below using the following scale. Note that there is no right or wrong answer. It is important to indicate your true perception in your responses for reliable results.

Not at all Knowledgeable – 1 2 3 4 5 6 7 8 9 10 – Extremely Knowledgeable

Knowledge

Criteria	1	2	3	4	5	6	7	8	9	10
K1. I understand GenAI has limitations in their ability to handle complex tasks.	1	2	3	4	5	6	7	8	9	10
K2. I understand GenAI can exhibit biases and unfairness in their output.	1	2	3	4	5	6	7	8	9	10
K3. I understand GenAI can generate output that is factually inaccurate.	1	2	3	4	5	6	7	8	9	10
K4. I understand GenAI may rely too heavily on statistics, which can limit their usefulness in certain contexts.	1	2	3	4	5	6	7	8	9	10
K5. I understand GenAI can generate output that is out of context or inappropriate.	1	2	3	4	5	6	7	8	9	10
K6. I understand GenAI has limited emotional intelligence and empathy, which can lead to output that is insensitive or inappropriate.	1	2	3	4	5	6	7	8	9	10

Effort Expectancy

Criteria	1	2	3	4	5	6	7	8	9	10
EE1. GenAI seems to be user-friendly.	1	2	3	4	5	6	7	8	9	10
EE2. My interaction with GenAI is comprehensible.	1	2	3	4	5	6	7	8	9	10
EE3. Deep technical understanding on GenAI is not required to utilize it.	1	2	3	4	5	6	7	8	9	10
EE4. I find learning to use GenAI would be manageable.	1	2	3	4	5	6	7	8	9	10
EE5. Using GenAI make it easy for me to generate and acquire knowledge	1	2	3	4	5	6	7	8	9	10
EE6. GenAI does not take much time to learn its usage.	1	2	3	4	5	6	7	8	9	10

Social Influence

Criteria	1	2	3	4	5	6	7	8	9	10
SI1. I consider the use of GenAI to be socially acceptable.	1	2	3	4	5	6	7	8	9	10
SI2. People who are important to me think that I should use GenAI.	1	2	3	4	5	6	7	8	9	10
SI3. I will be inclined to use the GenAI if my family members adopt it.	1	2	3	4	5	6	7	8	9	10
SI4. My peers do not encourage me to use GenAI.	1	2	3	4	5	6	7	8	9	10
SI5. I will consider using the GenAI if I am encouraged by my family members.	1	2	3	4	5	6	7	8	9	10
SI6. In general, my university will not support the use of GenAI.	1	2	3	4	5	6	7	8	9	10
SI7. People around me think I should use GenAI.	1	2	3	4	5	6	7	8	9	10
SI8. My colleagues encouraged me to use GenAI.	1	2	3	4	5	6	7	8	9	10
SI9. The people in my university told me that GenAI is helpful.	1	2	3	4	5	6	7	8	9	10

Facilitating Conditions

Criteria	1	2	3	4	5	6	7	8	9	10
FC1. I am not familiar what is GenAI and how to use it.	1	2	3	4	5	6	7	8	9	10
FC2. I think a specific person (or group) is available for assistance with the use of GenAI.	1	2	3	4	5	6	7	8	9	10
FC3. I can have an online help while using GenAI.	1	2	3	4	5	6	7	8	9	10
FC4. I have the resources necessary to use GenAI.	1	2	3	4	5	6	7	8	9	10
FC5. I think I can get help from the students or professors when I have difficulties on using GenAI.	1	2	3	4	5	6	7	8	9	10
FC6. I think I am not able to use GenAI on academic purposes.	1	2	3	4	5	6	7	8	9	10
FC7. I think that using GenAI fits well with the way I like to learn.	1	2	3	4	5	6	7	8	9	10
FC8. If I have problems using GenAI, I could solve them very quickly.	1	2	3	4	5	6	7	8	9	10
FC9. I have the knowledge necessary to use GenAI.	1	2	3	4	5	6	7	8	9	10

Behavioral Intention

Criteria	1	2	3	4	5	6	7	8	9	10
BI1. Utilizing GenAI enhances my learning experience.	1	2	3	4	5	6	7	8	9	10
BI2. I have used GenAI in the past for my academic queries.	1	2	3	4	5	6	7	8	9	10
BI3. I frequently rely on GenAI to find sources of information for my university assignments and duties.	1	2	3	4	5	6	7	8	9	10
BI4. I always find myself turning to GenAI when I need information for my university assignments and duties.	1	2	3	4	5	6	7	8	9	10
BI5. I intend to expand my use of GenAI in academic duties.	1	2	3	4	5	6	7	8	9	10
BI6. It is not worth recommending GenAI to other students for their academic activities.	1	2	3	4	5	6	7	8	9	10
BI7. In the future, my intention is to stop utilizing GenAI for academic purposes.	1	2	3	4	5	6	7	8	9	10
BI8. Continuing to use GenAI for academic purposes remains part of my plan.	1	2	3	4	5	6	7	8	9	10

To access the online copy of the actual data questionnaire:

Not Acceptable - 1 2 3 4 5 6 7 8 9 10 - Highly Acceptable

GenAI Acceptance

Criteria	1	2	3	4	5	6	7	8	9	10
GA1. I can accept GenAI based on its transparency and explainability.	1	2	3	4	5	6	7	8	9	10
GA2. I can accept GenAI based on its accuracy.	1	2	3	4	5	6	7	8	9	10
GA3. I can accept GenAI based on its value.	1	2	3	4	5	6	7	8	9	10
GA4. I can accept GenAI based on its decision-making capabilities.	1	2	3	4	5	6	7	8	9	10
GA5. I can accept GenAI based on its privacy and data security.	1	2	3	4	5	6	7	8	9	10
GA6. I can accept GenAI based on its benefit.	1	2	3	4	5	6	7	8	9	10
GA7. I can accept GenAI based on my previous experience on using it.	1	2	3	4	5	6	7	8	9	10
GA8. I can accept GenAI based on its social and ethical implications.	1	2	3	4	5	6	7	8	9	10
GA9. I can accept GenAI based on its accessibility.	1	2	3	4	5	6	7	8	9	10

Google form link: https://forms.gle/d3dmzKcQrszPeaUx7

QR code:

APPENDIX B

1. Are you in favor of the utilization of GenAI tools by students and educators in higher education? Why? do you think
2. How do the college students' usage of GenAI tools change the way faculty members teach and assess student learning? Could it lead to new approaches or assessment methods?
3. Is there a sense of urgency or future plans to the development of guidelines and policies regarding the students' use of GenAI tools in the university? Why? do you think
4. How can we establish comprehensive support structures and mechanisms to ensure both responsible and ethical utilization of GenAI tools in higher education institutions? Will there be provisions for educators and students such as training or seminars on ethical usage and effective incorporation of these tools into learning processes?

J B ESPIRITU 4/01/24