AI in higher education: Faculty perspective towards artificial intelligence through UTAUT approach

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ABSTRACT

Applications of AI in higher education have been around for several years, and numerous studies have looked at the pedagogical potential that these applications can offer to support the learning processes. However, there are still concerns and misunderstandings about acceptance in higher education, particularly among faculty members, despite the growing number of studies and their opportunities for supporting the educational and learning process. This paper aims to investigate the Behavioral Intention (BI) of Higher Education Institution faculty (HEI-faculty) towards adopting AI from a pedagogical perspective. The hypotheses in this paper were tested using a technology acceptance model with four major constructs: Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC), as well as the effects of four mediating variables: age, gender, experience, and voluntariness. The result has shown that the Behavioral Intention (BI) of adopting AI among HEI faculty has a strong positive significant correlation with PE, EE, SI, and FC. Interestingly, the social influence of adopting AI from colleagues has a strong influence on the use of AI for education. Thus, one of the proposed hypotheses was disproven. Furthermore, the result of this paper also suggests considerations for the future development of AI applications for HE.

1. Introduction

AI was first introduced in the 1950s at Dartmouth College in the United States (Wang, 2012). AI is a method to use computers to imitate human’s capability to think, plan, learn, reason, understand, identify, and solve simple to complex problems. According to McCarthy, any aspect of learning or intelligence can be mathematically illustrated in such detail that a computer can replicate it (Baker, Smith, & Anissa, 2019; Pedró, 2020). In addition, AI is a term used to portray a wide range of technologies and methods, including Machine Learning (ML), Natural Language Processing (NLP), Data Mining (DM), Data Analytics (DA), and Neural Networks (NN). It has a wide variety of mathematical and computational algorithms and does not explicitly imply any singular technology (Pedró, 2020). With the development and growth of modern computers, AI applications have become possible. As a result, it has attracted research interest and has been dubbed the “Top Technology of the 21st Century” (Yang, 2020; Yang, Huan, & Yang, 2020).

Since the beginning of the 4th Industrial Revolution, also described as the "Age of AI" (Beltramini, 2019), the research and application of AI-based solutions for modern-day issues have become the frontier for a game-changing technology, and this can be observed in many research fields, such as in healthcare (Davenport & Kalakota, 2019; Mohanty, Rashid, Mridul, Mohanty, & Swayamsiddha, 2020; Rampton, Mittelman, & Goldhahn, 2020; Sousa et al., 2021), smart transportation solutions (Miles & Walker, 2006), environmental issues (Vo, Hart, Laden, & Chiang, 2018), manufacturing and engineering (Lee, Davari, Singh, & Pandhare, 2018), supply-chain management solutions (Min, 2010), and in the education (Cheah, 2021; Kuleto, Ilić, Dedić, & Raketić, 2021; Li, 2017; Shuli, 2017). AI in Education (AIEd) has begun to emerge in educational institutions in the form of computer chatbots, which were introduced to provide students with automated responses to inquiries as well as learning support (Khare, Stewart, & Khare, 2018; Lin, Wooders, Wang, & Yuan, 2018).

1.1. AI applications in higher education institutions

In recent years AI in education has grown significantly, particularly in Higher Education Institutions (HEIs). It has been the focus of more than 30 years of research. Furthermore, there is considerable potential for AI applications in HEI (henceforth "AI-HEI") that will significantly impact the future of learning (Ali & Abdel-Haq, 2021; Huang, 2021). By 2022, AI research was predicted to expand by 43% (Ali & Abdel-Haq, 2021). Numerous research has concluded that AI-HEI can support students to better understand their cognitive skills and choose the best learning strategy for individualized instruction and independent learning (Ilić, Păun, Šević, Hadžić, & Jianu, 2021).

HEIs in the Philippines also embrace the idea of AI-HEI, and it is predicted that there will be an outpouring number of students interested in studying AI. One example is the study of Ang and Aragon (2020), which proposes a curriculum by developing an "AI-Enhanced Information Technology Program." The proposed "AI-enhanced IT Program" is anchored with the learners' spiritual dimension and the university's core values. Thus, it is essential to highlight that AI-HEI does not focus on the technology entirely but rather on the pedagogical, cultural, social, economic, ethical, and psychological dimensions of HEIs as well, making AI-HEI a cross-disciplinary field of research (Guan, Mou, & Jiang, 2020).

1.2. AI and higher education institution faculty. Is it viewed as a threat?

According to research by Dilmurod and Fazliddin (2021), AI does not compete with HEI faculty in students' skills and knowledge assessment. Instead, AI is a helpful tool that can improve communication and support in the educational process. In addition, AI can provide analysis for the most effective learning strategies customized to a specific student's learning path. Higher Education Institution faculty (henceforth "HEI-faculty") will continue as the frontline of higher education, and the misconception that AI is replacing them is said to be mistaken (Luckin, Holmes, Griffiths, & Forcier, 2016). Instead, HEI faculty is considered to be the driving force behind the adoption of AI in HE; thus, they must continue to take the lead behind such innovation (Zawacki-Richter, Marín, Bond, & Gouverneur, 2019).

However, it is advised that HEI-faculty training is a crucial aspect of enabling an effective AI-HEI. Still, there are many surrounding implications and concerns regarding AI applications in Higher Education Institutions, particularly regarding the adoption of HEI faculty (Dilmurod & Fazliddin, 2021; Pedró, 2020). Thus, this study presents a further effort to understand, the perception surrounding the acceptance of faculty towards AI application for higher education in the Philippines by exploring the BI in a pedagogical sense toward technological acceptance of AI.

The research is based on the Marinduque State College (MSC) since MSC is one of the many SUCs in the Philippines efforts to innovate the institution through a smart campus. An endeavor that would potentially adopt AI as one of the educational technologies to deliver higher education. With this, it is important to understand the perception of the faculty whether it could be a potential tool for the delivery of higher education or a threat to learning.

2. Literature review and hypothesis development

Adopting AI in a complex environment, particularly for HEIs-teachers is a challenging endeavor (Khare et al., 2018). Therefore, it is equally important to understand the HEI faculty's perception and BI toward adopting AI into the pedagogical setting.

2.1. The UTAUT model

A review of eight theories of technology acceptance was conducted in 2003 by Venkatesh et al. (2003) in an effort to integrate all the technology acceptance models at the time. The following models and theories are among them as follows: The Theory of Reasoned Action (TRA), the Theory of Planned Behaviors (TPB), the Technology Acceptance Model (TAM), the combination of TAM and TPB (C-TAM-TPM), the Model of PC Utilization (MPCU), the Innovation Diffusion Theory (IDT), the Motivational Model (MM), and the Social Cognitive Theory (SCT). In response, Venkatesh et al. (2003) proposed a novel theory called the "Unified Theory of Acceptance and Use of Technology" (UTAUT), which was referred to as a synthesis of all earlier models of technology acceptance and use (Momani, 2020).

Venkatesh et al.'s (2003) comprehensive explanation of technology acceptance and users' behavioral intentions towards new technology included important variables that can predict Behavioral Intentions (BI). Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Condition (FC) are the four main determining constructs that affect the Behavioral Intention (BI) towards a technology, according to the proposed UTAUT model.

2.2. Behavioral intention

Corresponding to the UTAUT model by Venkatesh et al. (2003), BI can determine how technology is accepted, and the four major constructs directly affect the perceived likelihood of technology acceptance. In addition, four mediating variables can affect the predictability of the four constructs: age, gender, experience, and willingness (Marikyan & Papagiannidis, 2021).

2.3. Performance expectancy

Performance Expectancy (PE) is defined as "the degree to which an individual believes that using the system will help gain in job performance" (Venkatesh et al., 2003, p. 159). It is the most significant predictor of BI in terms of adopting technology and is moderated by gender and age. In addition, PE is significant in both voluntary and mandatory settings.

The UTAUT model was used in a study by Wu, Zhang, Li, and Liu (2022) to determine college students' acceptance and willingness toward an environment with AI-assisted learning. The implementation of the AI-assisted learning environment in classrooms aims to support the development of novel pedagogical models. College students exhibit a "weak rejection" of an AI-assisted learning environment, according to the findings, indicating a strong acceptance of the technology. It is also discovered that the BI of college students to adopt AI-assisted learning is strongly predicted by EE, PE, and SI. The study's findings aided in risk communication and promoted the advancement of the learning environment with AI support.

Another study from Hao, Miao, and Yan (2021), investigates the willingness of school principals to adopt AI using the UTAUT model. By introducing innovation and perceived risk as an additional construct to explore the influencing factors of willingness to adopt AI in Education. The result reveals that the subjects have a strong willingness to adopt AI in Education, although it is also shown that the technological development of AI for education is currently low. Moreover, it is also revealed that PE and EE significantly affect the BI of adopting AI in Education. Performance expectancy has been observed to have a positive influence on behavioral intention. This could indicate that when AI can help educators in terms of teaching and learning in higher education, it could influence their behavioral intentions toward AI. Thus, the hypothesis has been suggested:

H1: Performance Expectancy (PE) has a positive significant effect on the Behavioral Intention (BI) of adopting AI among HEI faculty

2.4. Effort expectancy

Effort Expectancy (EE) is defined as "the degree of ease associated with the use of the system." Venkatesh et al. (2003, p. 159). A key predictor of technology acceptance, EE is a direct predictor of BI, moderated by gender, age, and experience. The UTAUT model was used by Tran et al. (2021) to create a theoretical framework for investigating medical students' BI to use an AI-based diagnosis support system. by using an online cross-sectional survey designed using the UTAUT model to survey 211 undergraduate medical students. The findings showed that the BI of undergraduate medical students adopting the AI-based Diagnosis Support System was positively correlated with EE. The study also highlights students' positive BI towards using an AI-based diagnosis support system as well as the beneficial impact of SI on BI.

In a different application of UTAUT, Zhang (2020) applied the UTAUT model to verify the impact and BI of using AI in music by using PE and EE as the major constructs. The research also added two new variables to UTAUT to fit the current market situation in China. In achieving the goal, 345 questionnaires were accumulated from experienced music creators, and it was revealed that three influential factors would affect users' intentions to adopt AI. These include Perceived Innovation (PI), PE, and EE. The literature provided insight that the ease of using AI for education could predict an influence on behavioral intention. Reviewing literature on the application of the UTAUT model, it is highlighted that EE and PE have a significant effect on BI toward AI. Thus, the hypothesis has been suggested:

H2: Effort expectancy (EE) has a positive significant effect on the behavioral intention (BI) of adopting AI among HEI faculty

2.5. Social influence

According to Venkatesh et al. (2003), Social Influence (SI) refers to "The extent to which an individual perceives that society needs him to adopt a particular technology." (p. 159). When using the new system is required, people might do so out of obligation rather than choice. It is moderated by factors such as gender, age, experience, and voluntariness.

At Hashemite University, a public university in Jordan, Abbad (2021) used the UTAUT model to analyze students' intention to use an e-learning system using the four major determinants: PE, EE, SI, and FC. 370 undergraduate students' data were collected, and structural equation modelling techniques were used to analyze it. The outcome demonstrates that the students' BI to use Moodle is significantly influenced by PE and EE. It's interesting to note that BI is unaffected by SI. The impact of FC on students' BI when using Moodle is also made clear. From the result of the study, the UTAUT model thus provides a valuable tool that supports the university in reassessing its decision-making and helps prepare other education institutions to adopt e-learning systems.

A comparable result was found in the study by Nain (2021). The study examines students' BI to accept social media learning using the UTAUT model. 279 Delhi University undergraduates participated in the study. The findings showed that students' perceptions of PE, EE, and FC, but not in terms of SI, have a significant impact on their BI to use social media as a learning platform. From the literature reviewed, it can be observed that social influence could predict a negative influence on behavioral intention. Thus, a hypothesis has been suggested:

H3: Social Influence (SI) has no significant effect on the Behavioral Intention (BI) of adopting AI among HEI faculty

2.6. Facilitating conditions

Facilitating Condition (FC) is described as the "degree to which an individual believes that an organization and technical infrastructure exist to support the use of the new technology" (Venkatesh et al., 2003, p. 159). FC has a significant direct effect on BI and is moderated by age and experience.

In the study of Qazi, Raza, Khan, and Salam (2021), the UTAUT model was applied to examine the adoption level of e-learning systems among students in developing countries, as it is perceived as educational as well, without the constraints of time, distance, and resources. The data were collected through the survey method and processed through confirmatory factor analysis and partial least structural equation modeling. The results revealed that PE, EE, habit, knowledge acquisition, knowledge sharing, and FC are positively linked to BI to the students' acceptance of e-learning systems. Similarly, Li and Zhao (2021) conducted a study to analyze the factors influencing the BI of using Massive Open Online Courses (MOOCs) among students. The study implemented the UTAUT model to create a survey questionnaire. It was then distributed to 312 students to verify the hypotheses proposed. The result shows that PE, EE, and FC had significant positive effects on the BI of the students using MOOCs. From the reviewed literature and studies, it is revealed that SI has a less significant impact, while FC directly impacts the BI towards adopting technology. Thus, a hypothesis has been suggested:

H4: Facilitating Condition (FC) has a positive significant effect on the Behavioral Intention (BI) of adopting AI among HEI faculty

2.7. Research gap and opportunity

According to the literature review, the UTAUT model provides an extensive approach to assessing the degree to which individuals accept and use new technologies (Venkatesh et al., 2003; Venkateshf, Davis, & Morris, 2007). The UTAUT model is suitable for this research since it has demonstrated its effectiveness in studies on BI towards technology adaptation (Abbad, 2021; Hao et al., 2021; Tran et al., 2021; Wu et al., 2022; Zhang, 2020).

Additionally, the reviewed literature places a strong emphasis on the perspective and BI of the student. Consequently, it is equally crucial to comprehend the educators' point of view. This study will concentrate on comprehending the BI of faculty towards implementing AI in a teaching environment. The UTAUT model can shed light on the faculty's viewpoint and BI's approach to incorporating AI into their instructional and evaluation strategies.

2.8. Objectives of the study

This study used the UTAUT model with PE, EE, SI, and FC as the main constructs to identify the factors that motivate the BI of faculty at Marinduque State College to incorporate AI into their teaching and assessment strategies.

Faculty from the Institute of Information Systems and Technology (IIST), Institute of Engineering (IE), and Department of Industrial Technology (DIT) within the Marinduque State College (MSC) College of Engineering, Information, and Industrial Technology (CEIIT) were identified in order to achieve the objective. The majority of the faculty at Marinduque State College are members of the CEIIT. In order to examine and test the hypothesis, a quantitative approach was also used. A narrative of the research variables based on the respondent's responses and the distribution of respondents according to various demographic variables were both presented using descriptive statistics.

2.9. Proposed hypothesis

Several studies have applied the UTAUT model to examine the respondents' BI and acceptance of AI in Education. (Abbad, 2021; Hao et al., 2021; Li & Zhao, 2021; Nain, 2021; Qazi et al., 2021; Tran et al., 2021; Wu et al., 2022; Zhang, 2020). From the reviewed literature, figure 1.0 shows the proposed conceptual model for the study:

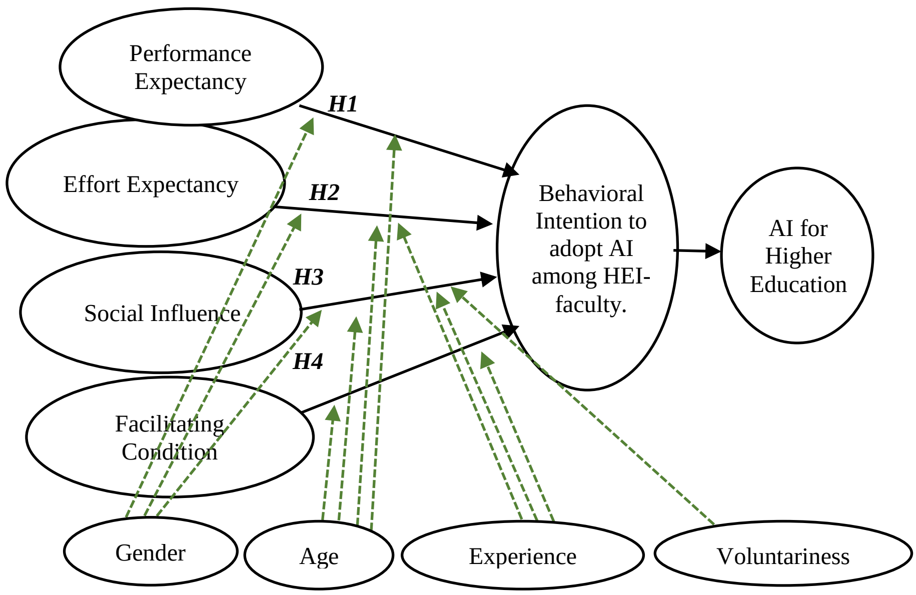

Figure 1. Modified UTAUT Model adopted from Venkatesh et al. (2003)

Guided by the proposed research framework, the following hypothesis has been tested:

H1: PE has a positive significant effect on the BI of adopting AI among HEI faculty

H2: EE has a positive significant effect on the BI of adopting AI among HEI faculty

H3: SI has no significant effect on the BI of adopting AI among HEI-faculty

H4: FC has a positive significant effect on the BI of adopting AI among HEI faculty

3. Methodology

The research model includes five major constructs, these include PE, EE, SI, FC, BI, and four mediating variables. The analysis was based on the UTAUT model (Marikyan & Papagiannidis, 2021; Venkatesh et al., 2003). Additionally, a five-point Likert scale was used to interpret survey questionnaire items (1 = Strongly Disagree, 2 = Disagree, 3 = Neither Agree nor Disagree, 4 = Agree, and 5 = Strongly Agree).

3.1. Data collection method

The survey questionnaires were distributed online (by sending a Google link through faculty group chats) and were written with English and Tagalog translations. Following the distribution and collection of the survey forms for initial review, it was further improved comprehensively based on the comments of the respondents. The survey questionnaire was then randomly and in no particular order distributed to the faculty members of the Institute of Information Systems and Technology (IIST), Institute of Engineering (IEng), and Department of Industrial Technology (DIT) within the College of Engineering, Information, and Industrial Technology (CEIIT).

3.2. Sample size and statistical method

The identified population consists of HEI educators from three (3) different institutions that are part of Marinduque State College's (MSC) College of Engineering, Information, and Industrial Technology (CEIIT). With a total of one hundred thirty-six (136), the CEIIT has the most faculty. The faculty members were split among the CEIIT with forty-three (43) coming from the Institute of Engineering (IEng), sixty (60) from the Department of Industrial Technology, and thirty-three (33) from the School of Information Systems and Technology (IIST).

A sample size of at least 101 was determined using Slovin's formula with a 5% margin of error (sample size = N/(1+Ne2), e = 0.05). Additionally, the survey questionnaires were given out to all 136 potential respondents from CEIIT in order to account for potential non-responses. The data was also subjected to statistical and descriptive analysis, reliability, consistency, and convergent validity testing.

4. Result and discussion

The surveys were distributed to all 136 CEIIT faculty members using Google Forms. A total valid sample of 104 participants, out of 110 total respondents, were used in this study's data collection.

4.1. Demographic characteristics of the respondents

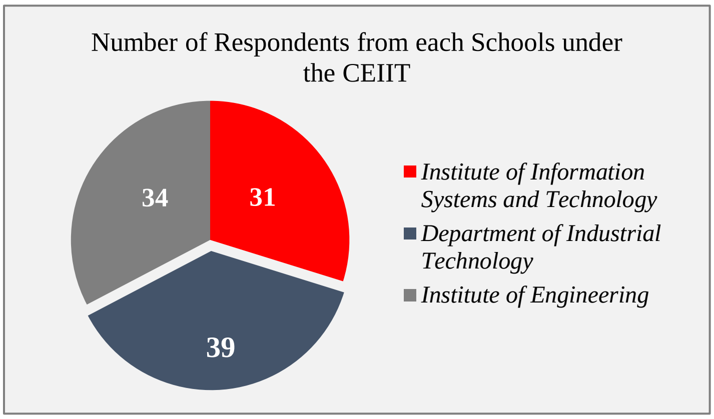

Figure 2. Number of respondents from CEIIT

Figure 2 shows the number of respondents from CEIIT. 39 of the total 104 respondents or 38% are from the Department of Industrial Technology (DIT) which represents the majority of the respondents. 34 of the total 104 respondents or 32% are from the Institute of Engineering (IEng) which represents the second largest number of respondents, and 31 of the total 104 respondents, or 30% are from the Institute of Information Systems and Technology (IIST).

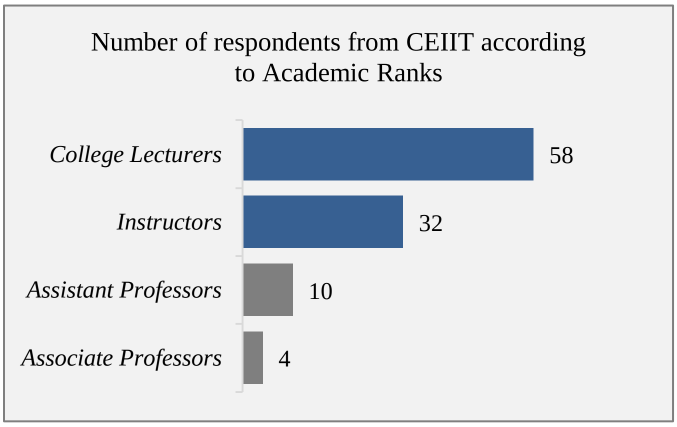

Figure 3. CEIIT Faculty Academic Ranks

Figure 3 shows the number of respondents and their identified academic ranks. 58 of the total 104 respondents or 56% are College Lecturers representing the majority of the respondents. 32 of the total 104 respondents or 31% are Instructors representing the second largest number of respondents. 10 of the total 104 respondents are Assistant Professors while 4 of the 104 respondents or 4% are Associate Professors representing the least number of respondents.

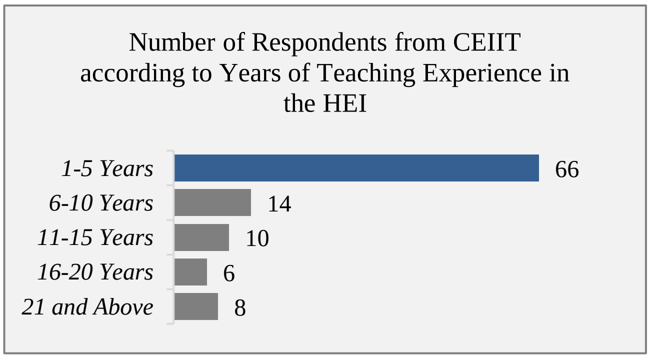

Figure 4. Number of respondents from CEIIT according to years of teaching experience in the HEI

Figure 4 shows the number of respondents from CEIIT and their associated years of teaching experience in the HEI. 66 of the total 104 respondents or 63% have at least 01 - 05 years of teaching experience in the HEI representing the majority of the respondents. The second largest number of respondents, 14 of the identified 104 respondents or 13%, have at least 06 to 10 years of teaching experience. 10 of the identified 104 respondents or 9% have 11 to 15 years of teaching experience, while 6 of the total 104 respondents, or 6% have 16 to 20 years of teaching experience which represents the least number of respondents. Lastly, 8 of the total 104 respondents have 21 and more years of experience teaching in the HEI, all of which are not far behind.

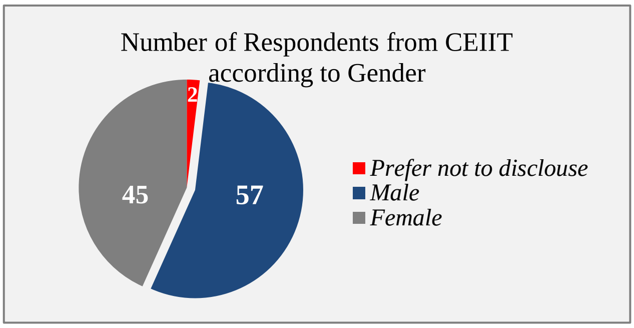

Figure 5. Number of respondents according to Gender

Figure 5 shows the total number of respondents from CEIIT according to their gender. 57 of the total 104 respondents or 55% are male which represents the majority of the respondents, 45 of the 104 respondents, or 43% are female while 2 of the 104 respondents prefer not to disclose their gender.

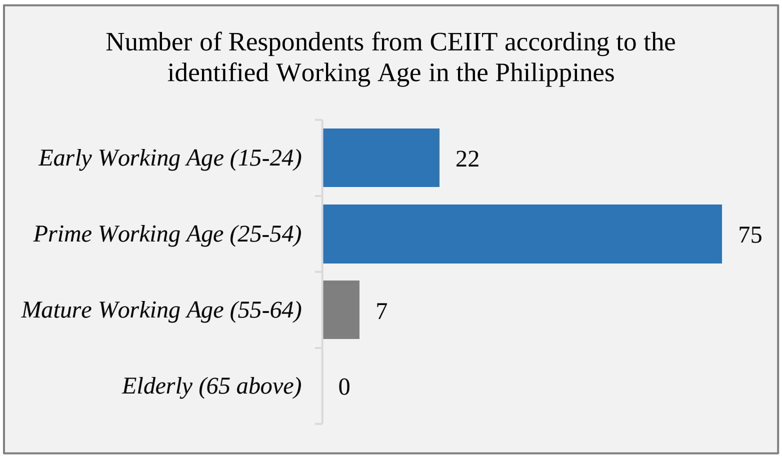

Figure 6. Number of respondents from CEIIT according to the identified working age in the Philippines

The working age population in the Philippines is between the ages of 15 and 64 and can be divided into different categories such as early working age, prime working age, mature working age, and elderly, according to the Philippine Statistics Authority (Philippine Statistics Authority, 2017), an agency of the government in the Philippines tasked with providing timely and accurate statistics required for decision-making in all aspects of Filipino life.

Figure 6 shows the number of respondents from CEIIT who are grouped into working-age categories. 75 of the 104 respondents or 72% are in their prime working age from 25 to 54 years old, representing the majority of the respondents. 22 of the 104 respondents or 21% are in their early working age while 7 of the 104 respondents or 7% are currently in their mature working age. It is also observed that age 22 is the youngest and 62 is the highest age in the identified 104 respondents.

4.2. Model evaluation

To measure the internal consistency reliability of the model, two methods were applied, which are Cronbach's alpha test and the construct reliability test. It is suggested that the result of the internal consistency reliability test must be 0.7 or higher to be acceptable (Chin, 1998). First, based on the calculations performed in Cronbach's Alpha, the test results are shown in Table 1.

PE and BI both have a score of 0.967 which has the highest score in the test results. EE has a test result of 0.959 as the second highest test score, followed by SI which has a 0.921 test score. Lastly, FC has a test score of 0.841 as the lowest test result. Regardless, all the tested variables have an excellent level of reliability.

In the result of the internal consistency reliability test using Cronbach's Alpha as shown in Table 1, all the variables tested in the study were in the range between 0.7 and 0.9. It can be inferred that these variables have excellent reliability and met Cronbach's Alpha requirements.

Table 1

Cronbach's Alpha test results

Variables	**Cronbach's Alpha (> 0.70)**	**Interpretation**
Performance Expectancy (PE)	0.967	Excellent
Effort Expectancy (EE)	0.959	Excellent
Social Influence (SI)	0.921	Excellent
Facilitating Condition (FC)	0.841	Excellent
Behavioral Intention (BI)	0.967	Excellent

Second, the result of the internal consistency reliability with the construct reliability test is shown in Table 2. All the tested variables used in the study were also in the range between 0.7 and 0.9. It can be interpreted that these variables have excellent reliability and fulfill the requirements of the construct reliability test (Chin, 1998). BI has the highest test result of 0.938, followed by PE, which has a test score of 0.918. The results are both consistent with the test result of Cronbach's alpha being the two variables with the highest test results. EE has a test score of 0.905, the third highest test score, followed by SI with a test score of 0.849. Lastly, FC has the lowest test score of 0.839. The result of FC is also consistent with the result of Cronbach's Alpha test in Table 1 which shows that FC is the lowest test score.

The Construct Reliability test results generally show that all values were above 7.0, which also satisfies the suggested standard by Chin (1998). The outcome suggests that the variables can be measured and have sufficient internal consistency.

Table 2

Construct reliability test results

Variables	**Construct reliability (> 0.70)**	**Interpretation**
Performance Expectancy (PE)	0.918	Reliable
Effort Expectancy (EE)	0.905	Reliable
Social Influence (SI)	0.849	Reliable
Facilitating Condition (FC)	0.839	Reliable
Behavioral Intention (BI)	0.938	Reliable

The results of the convergent validity test's Average Variance Extract are shown in Table 3. It is proposed that the valid value of the result must be greater than 0.50. (Fornell & Larcker, 1981). BI has the highest test score (0.836), followed by PE, which has a test score of 0.789, according to the results in Table 3. This is also consistent with the previous test results in Tables 1 and 2, where PE and BI had the highest testing scores. EE has a test score of 0.761, and SI has a test score of 0.651. Lastly, FC has the lowest test score of 0.635. It can also be observed that FC consistently has the lowest test scores. Regardless, all the tested variables have met the standard of the convergent validity test, and it can be concluded that there is sufficient convergent validity (Fornell & Larcker, 1981).

Table 3

Average variance extract test results

Variables	Average variance extracted (> 0.50)	Interpretation
Performance Expectancy (PE)	0.789	Valid
Effort Expectancy (EE)	0.761	Valid
Social Influence (SI)	0.651	Valid
Facilitating Condition (FC)	0.635	Valid
Behavioral Intention (BI)	0.836	Valid

4.3. Hypothesis test and discussion of the results

Hypotheses are tested by performing significance and correlation tests. This test enables the researcher to comprehend how the variables relate to one another and how the covariates in the model affect the results. To comprehend the relationship between the variables and the mediating effect of covariates on the constructs, partial correlation analysis was carried out using SPSS, as shown in figure 1. In addition, a scatterplot was applied to visualize the statistical significance and correlation of the tested variables.

4.3.1. Testing the result of Hypothesis 1

Table 4

Hypothesis 1 testing result

covariates	path	correlation	significance (2-tailed)	conclusion
-none-[a]	PE→ BI	0.845	0.000	Strong Positive Significance
gender, age	PE→ BI	0.845	0.000	Strong Positive Significance

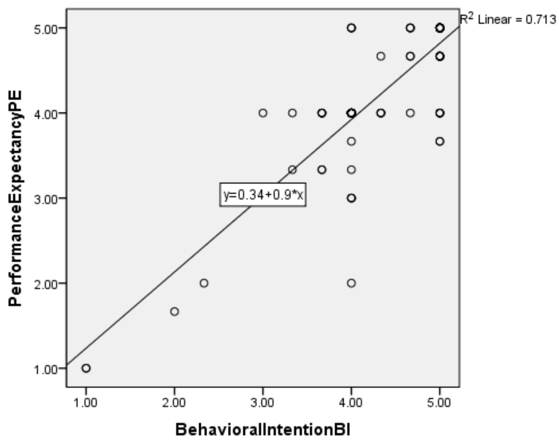

Figure 7. Performance Expectancy (PE) and Behavioral Intention (BI) scatterplot

Performance Expectancy (PE)

Based on the test result shown in Table 4, the test result of hypothesis 1: PE and BI were first tested without the covariates. The test result shows that PE has a strong positive significant correlation with BI with a p-value of less than 0.05 and with a strong correlation of 0.845. In Figure 7, it can be observed that the trend line in the scatter plot is in linear trend, supporting the positive correlation between the variables.

In addition, it can be observed in Table 4, that when age and gender were added as the covariates, the results did not change. This can be interpreted that age and gender have no mediating effect on the correlation between the variables. This concludes that hypothesis 1 is true. PE has a positive significant effect on the BI of adopting AI among HEI faculty. In addition, the age or gender of the respondents has no significant impact on the correlation.

According to Venkatesh et al. (2003), PE is the strongest predictor of BI in adopting technology in either voluntary or mandatory settings, thus supporting the result of the hypothesis. This can also be observed in the study of Kuleto, Ilić, Dumangiu, et al. (2021) where the respondents strongly believe AI in higher education can enhance individualized learning in a variety of ways; by developing students' skills; providing collaborative learning environments within the HIEs, thus potentially improving the institutions' efficiency in the academic settings. Additionally, the age and gender of the respondents do not have any negative impact on the adoption of AI in academic settings. HEI faculty strongly believe that AI can help in the learning and assessment process.

One respondent from this study, 29 years old and with 05 years of teaching experience in HEI, stated: "*I think it is only reasonable that we dive into a more technological-aided way of teaching given that technology is quickly advancing, and we are supposed to catch up with these said advancements. I think AI technology will be beneficial for the educator who is willing to integrate it into their pedagogy as it will give ease to their teaching and will also help the students with their learning.*" Moreover, it was stated that HEI faculty strongly believe that AI can potentially discover new ways their students learn and can advise in tailoring their teaching methods to meet their goals.

4.3.2. Testing the result of Hypothesis 2

Table 5

Hypothesis 2 testing result

covariates	**path**	**correlation**	**significance (2-tailed)**	**conclusion**
-none-[a]	EE→ BI	0.815	0.000	Strong Positive Significance
gender, age, experience	EE→ BI	0.811	0.000	Strong Positive Significance

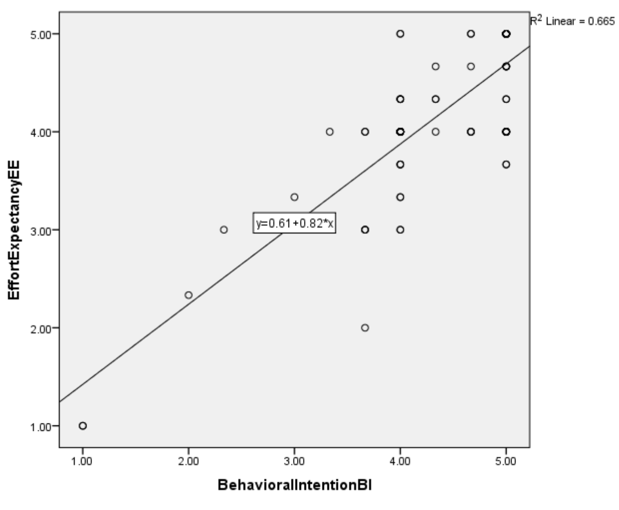

Figure 8. Effort Expectancy (EE) and Behavioral Intention (BI) scatterplot

Effort Expectancy (EE)

Based on the result shown in Table 5, test results of hypothesis 2: EE, and BI were first tested without the covariates as well. The test result shows that EE also has a strong positive significant correlation with BI with a p-value of less than 0.05 and a strong correlation of 0.815. In addition, in Figure 8, it can be observed that the trend line in the scatter plot is also in a linear trend, supporting the positive correlation between the variables. In addition, it can be observed in Table 5, that when covariates were added to the test, the results of the correlation slightly dropped from 0.815 to 0.811. This can be interpreted as age, gender & experience having a slight negative mediating effect in the correlation between the variables but not significant.

This concludes that hypothesis 2 is also true. EE has a positive significant effect on the BI of adopting AI among HEI faculty, however, age, gender, and experience will have a slight negative mediating effect on the BI. Venkatesh et al. (2003) explained that EE is the degree of ease associated with the use of a system. When a particular user of a new system finds that the technology is difficult to use, it may influence the adoption of the technology regardless of the mediating factors, thus making EE a direct determinant and a crucial predictor of BI. Chao (2019) demonstrates the effect of EE on the BI of adopting mobile-based learning among the respondents. The result reveals that when a particular user finds a new system engaging, easy, and enjoyable to use and considers it to improve their learning performance and effectiveness, their BI towards the technology is significantly increasing. The study further concludes that for future development of any technology in the academic setting, ease and enjoyment of the technology shall be considered a priority. Another respondent from this study, 26 years old and with at least 05 years of teaching experience in the HEI, stated: "*I hope that AI can make the learning process more enjoyable not only to students but also to the teachers.*"

Moreover, several more studies also confirmed the positive effect of PE and EE in BI, thus further supporting the result of this study (Hoque & Sorwar, 2017; Šumak & Šorgo, 2016).

4.3.3. Testing the result of Hypothesis 3

Table 6

Hypothesis 3 testing result

covariates	**path**	**correlation**	**significance (2-tailed)**	**conclusion**
-none-[a]	SI→ BI	0.762	0.000	Strong Positive Significance
gender, age, experience, voluntariness	SI→ BI	0.766	0.000	Strong Positive Significance

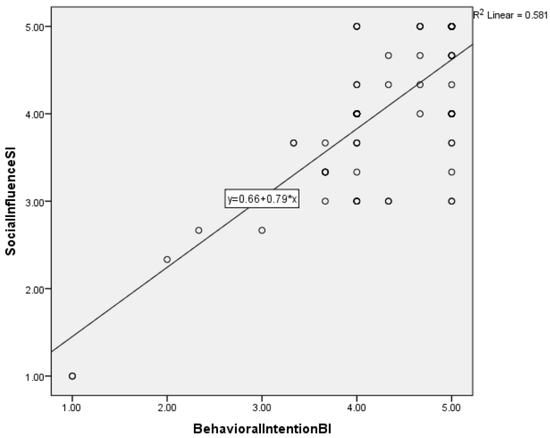

Figure 9. Social Influence (SI) and Behavioral Intention (BI) scatterplot

Social Influence (SI)

Based on the result shown in Table 6, the test result of hypothesis 3: SI and BI were first tested without the covariates. Interestingly, SI showed a strong positive correlation with BI with a p-value of less than 0.05 and a strong correlation of 0.762. It can be observed also in Figure 9 that the trend line in the scatterplot is in linear trend, supporting the positive correlation between the variables.

Additionally, it can be examined in Table 6, that when covariates were added to the test, the result of the correlation slightly increased from 0.762 to 0.766. This can be interpreted that the covariates have a positive mediating effect on the correlation between the variables. This concludes that hypothesis 3 is false. SI has a positive significant effect on the BI of adopting AI among HEI faculty, and the age, gender, experience, and voluntariness of the respondents make a positive impact on the BI. SI can directly influence the intention to adopt technology, especially in a mandatory setting as a compliance but not in a personal preference. (Venkatesh et al., 2003). This influence can be from superiors, other faculty, or peers.

The result is consistent with the study of Qazi et al. (2021), explaining that encouraging influences of social groups and peers will promote technology adoption, especially when they believe that their performance will improve without extra effort. The research also found that SI is a significant predictor of BI, supporting the outcome of hypothesis 3. According to Qazi et al. (2021), more HEIs are being urged to adopt technology-based learning systems as a result of the pandemic. The study's results also show that participants are eager to experiment with new technologies in the classroom if institutions continue to promote technology-based education.

4.3.4. Testing the result of Hypothesis 4

Table 7

Hypothesis 4 testing result

covariates	**path**	**correlation**	**significance (2-tailed)**	**conclusion**
-none-[a]	FC→ BI	0.856	0.000	Strong Positive Significance
age, experience	FC→ BI	0.855	0.000	Strong Positive Significance

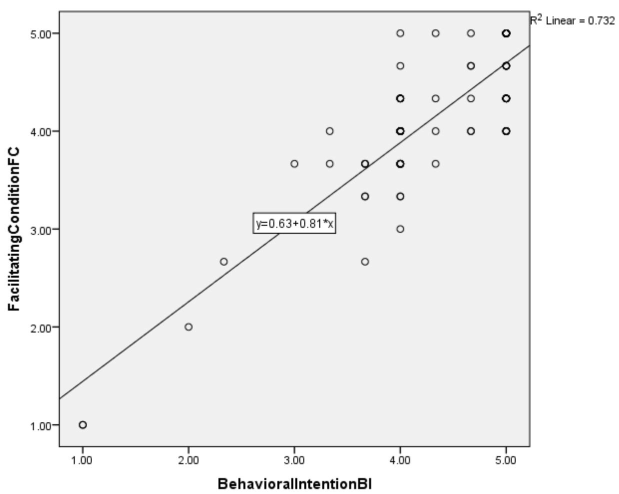

Figure 10. Facilitating Condition (FC) and Behavioral Intention (BI) scatterplot

Facilitating Condition (FC)

According to the test result in Table 7, the FC and BI were initially examined independently of the variables. With a p-value of less than 0.05 and a strong correlation of 0.856, the results demonstrate that the FC also has a significant positive relevance in the BI. Figure 10 further shows that the scatterplot's trend line follows a linear pattern, confirming the assumption that the variables are positively correlated. Table 7 also shows that the outcome of the test for the correlation marginally fell from 0.856 to 0.855 when variables were added, which is essentially no impact.

This concludes that hypothesis 4 is also true. FC has a positive significant effect on the BI of adopting AI among HEI faculty; thus age and experience of the respondents make little to no impact on the BI. Venkatesh et al. (2003) explained that if an individual or an organization believes that there is an adequate technical infrastructure to support the use of new technologies, it will have a significant impact on the adoption and BI toward new technology.

One respondent of this study, 30 years old and with at least 07 years of teaching experience in the HEI stated: "*I hope that AI will be implemented and be supported by the institution since it will be helpful both to students and instructor*". Li and Zhao (2021) further stated that FC does have a positive influence on the BI of adopting a new technology, thus supporting the result of hypothesis 4. In order to support the successful adoption of AI applications in academic settings, the study also recommends that Universities consider providing sufficient infrastructural facilities, resources, computer equipment, and smooth network links.

4.3.5. Summary of the Hypotheses test results

Table 8 shows the summary of the tested hypothesis of this study. Hypotheses 1, 2, and 4 are tested and proven to be true while hypothesis 3 is revealed as false.

Table 8

Summary of the hypotheses test results

Hypotheses	**path**	**Results**
(H1): Performance Expectancy (PE) has a positive significant effect on the behavioral intention of adopting AI among HEI faculty	PE→ BI	True
(H2): Effort Expectancy (EE) has a positive significant effect on the behavioral intention of adopting AI among HEI faculty	EE→ BI	True
(H3): Social Influence (SI) has no significant effect on the behavioral intention of adopting AI among HEI-faculty	SI→ BI	False
(H4): Facilitating Condition (FC) has a significant positive effect on the behavioral intention of adopting AI among HEI faculty	PC→ BI	True

5. Practical value and future research

This study used the Unified Theory of Acceptance and Use of Technology (UTAUT) approach to evaluate the BI and perspective of HEI faculty towards the pedagogical use of AI in Higher Education. According to the results of the hypothesis tests, PE, EE, SI, and FC all have a positive effect on HEI faculty members' Behavioral Intentions (BI) to embrace AI.

Marinduque State College is one of many HEIs in the Philippines that is currently moving toward a "Smart-Campus". An endeavor that will digitalize the teaching process, learning process, and administrative tasks and promote technology-based solutions to support high-quality education. The result of the study reveals that there is a strong acceptance of AI applications at Marinduque State College. Moreover, PE shows that the faculty strongly believes AI will help them assist in their teaching and assessment strategies to support the learning of the students, while EE suggests, that AI applications in teaching and learning should consider the enjoyment and ease of use in the future development of AI for Higher Education for both faculty and the learners. SI also reveals that the support of the Institution in AI for higher education has a significant impact on its implementations, while FC suggests that the Institution should consider adequate technical infrastructure in support of the success of implementing AI applications in HEIs.

For future development of AI applications for Higher Education settings, it is suggested to consider the following viewpoints. Moreover, this study only unveiled the faculty perspective towards AI application in Higher Education. Additionally, it is suggested to extend and conduct the study to the students and administrators of the HEIs and to include additional constructs such as Hedonic Motivation (HM), Price Value (PV) and Habit (H) to further explore the BI towards AI applications in higher education.

6. Abbreviations

AI	Artificial Intelligence
UTAUT	Unified Theory of Acceptance and Use of Technology
HEIs	Higher Education Institutions
BI	Behavioral Intention
PE	Performance Expectancy
EE	Effort Expectancy
SI	Social Influence
FC	Facilitating Conditions
AIEd	Artificial Intelligence in Education
AI-HEI	Artificial Intelligence Applications in Higher Education Institutions

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