Generative-AI, a Learning Assistant? Factors Influencing Higher-Ed Students' Technology Acceptance

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Abstract: This study investigates the factors influencing the adoption of Generative-AI tools amongst Thai university students, employing the Technology Acceptance Model (TAM) as a theoretical framework. Data from 911 higher education students from 10 different Thai Universities Health Sciences, Sciences and Technology, Social Sciences and Humanities, and Vocational Fields were analysed via Structural Equation Modelling (SEM). The instrument used in collecting the data was a questionnaire. Results indicated that Expected Benefits, Perceived Usefulness, Attitude Toward Technology, and Behavioural Intention all significantly impacted student adoption of Generative AI. Intriguingly, Perceived Ease of Use was negatively correlated with Perceived Usefulness, challenging conventional TAM assumptions. This study underscores the need to address language barriers, foster a culture of innovation, and establish ethical guidelines to promote responsible AI use within education. Despite inherent limitations, this research contributes to our understanding of AI adoption in educational settings and helps inform strategies for equitable access and responsible innovation. The result demonstrated that the easier a tool was to use, the less value leaners seemed to see in it for their learning process. It can be implied that as Generative-AI get more intuitive, learners think they're less helpful. These finding challenges a few of those assumptions we usually make within the TAM model. It also points out the characteristic of learners which affects their learning preferences and expectation. Another finding showed the impact of language barrier on non-native English speaker that obstruct the user experience in AI services. Moreover, the role of universities in fostering both AI integration for learning for and the ethical implementation of Generative AI. By providing a supportive environment that encourages AI experimentation, redesign learning, empowering learners and faculty instructors to investigate how Generative AI can be applied across disciplines, and developing guidelines for ethical use, universities play a critical role in shaping the effective and responsible integration of AI into the next educational landscape.

Keywords: Artificial Intelligence in education, Educational technology, Generative-AI, Student perceptions, Technology Acceptance Model, SEM research

1. Introduction

Education is an ever-evolving field significantly influenced by technological advancements. One of the pivotal drivers of change in educational development has consistently been technology (Dwivedi et al., 2021; Murugesan and Cherukuri, 2023). In this continuum of technological evolution, Artificial Intelligence (AI) has emerged as a transformative force, reshaping learning experiences and pedagogical approaches.

Recent advancements have seen the rise of Generative-AI, a subset of AI that autonomously creates content and data, distinguishing itself from other AI forms primarily focusing on data analysis or interpretation. This type of AI has the unique capability to generate new, personalised content, thereby offering significant potential to

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revolutionise educational methodologies and learning experiences (Cooper, 2023; Dai, Liu and Lim, 2023; Zawacki-Richter et al., 2019).

However, integrating Generative-AI into the education sector is not without challenges. These include the need for a comprehensive approach to ensure sustainable development, inclusivity, and equity in AI applications within education (Ahmad et al., 2021; Dai, Liu and Lim, 2023; UNESCO, 2023a, UNESCO 2023b). Additionally, there is a pressing need for inclusive data systems and adequate preparation of educators and students for an AI-enhanced educational landscape (Hutson et al., 2022; Rasul et al., 2023).

The potential of Generative-AI in education is particularly notable in creating personalised and unique educational materials. It can understand and adapt to individual students' learning patterns and needs, offering customised learning experiences that can significantly enhance engagement and learning outcomes (Celik et al., 2022; Gimpel et al., 2023). Such personalised approaches can lead to more effective learning, catering to individual preferences and learning styles, thereby potentially improving the overall quality of education.

Nevertheless, the adoption of Generative AI in higher education, especially in Thailand, is still nascent. There are various challenges to its widespread adoption, including concerns over its ability to understand and interpret complex educational content, ethical considerations, issues of plagiarism, and maintaining academic integrity (Chan and Hu, 2023; Nguyen, 2023; Wang et al., 2023; Su and Yang, 2023).

Addressing these challenges, this study explores the factors influencing the adoption of Generative-AI technologies in Thai higher education. It seeks to understand how Thai higher education students perceive Generative-AI and identify the key factors influencing its acceptance and integration into educational practices. By examining these factors, the study intends to contribute valuable insights toward developing effective strategies that enhance learning outcomes, ensure equitable access to AI's benefits, and maintain academic integrity in an increasingly AI-integrated educational landscape (Song, 2024).

This paper presents the factors influencing the Technology Acceptance Model (TAM) amongst Thai university students, by Structural Equation Modelling to clarify the relationships that reflect the actual use of Generative-AI. This study reviews related literature to identify the factors in the development of a research framework and hypotheses between TAM and Generative-AI. The outlines are included the research methodology, sample sampling procedures, instruments, and data analysis. The results, discussion, and implications are subsequently presented, emphasising the key findings on the relationships between TAM factors. This paper concludes with recommendations for the application of Generative-AI in higher education, as well as suggestions for future research and a discussion of the study's limitations.

1.1 Research Questions

RQ1: How do higher education students perceive the Expected Benefit, Perceived Usefulness, and Perceived Ease of Use of Generative-AI, and how do these perceptions influence their Attitude Toward Using and Behavioural Intention to use Generative-AI, as well as its Actual Use?

RQ2: What are the relationships between Expected Benefit, Perceived Usefulness, and Perceived Ease of Use of Generative-AI, and Behavioural Intention, and how do these relationships affect the Actual Use of Generative-AI in higher education?

RQ3: How do Expected Benefits, Perceived Usefulness, Perceived Ease of Use, and Behavioural Intention influence the adoption and integration of Generative-AI technologies in higher education?

1.2 Research Objectives

This research aims to investigate the factors influencing the adoption of Generative-AI amongst higher education students using the TAM. The specific objectives are:

- To study the Expected Benefit, Perceived Usefulness, Perceived Ease of Use, Attitude Toward Using Generative-AI, Behavioural Intention, and Actual Use of Generative-AI amongst higher education students.
- To study the relationship between Expected Benefit, Perceived Usefulness, Perceived Ease of Use, Attitude toward Generative-AI, Behavioural Intention, and Actual Use of Generative-AI amongst higher education students.
- To determine the influences of Expected Benefit, Perceived Usefulness, Perceived Ease of Use, and Behavioural Intention towards Generative-AI adoption.

2. Literature Review and Hypothesis Development

2.1 Generative-AI in Higher Education

Generative-AI has been increasingly integrated into the educational sector, providing a transformative approach to teaching and learning (Lim et al., 2023). It has been utilised to create personalised learning experiences, enhance student engagement, and improve educational outcomes (Gustafson, 2023). Generative-AI tools, such as chatbots and virtual tutors, have facilitated interactive learning environments, provided instant feedback, and supported personalised learning paths (Gustafson, 2023). Generative-AI can be divided into four main types: text generation, image creation, and video production (Jiayang Wu et al., 2023).

- *Text generation*: Generative-AI includes the areas of structured composition, imaginative writing, and conversational scripting as its primary branches such as ChatGPT, Google Gamini, Claude, etc.
- *Image generation*: Utilizing Generative-AI allows individuals to modify and introduce additional components into their images in response to specific instructions such as DALL-E, Midjourney, etc.
- *Sound generation*: Generative-AI in audio involves two main types: synthesis of speech from text and replicating existing voices such as MURF, Soundraw, Botnoi, etc.
- *Video generation*: The application of Generative-AI in creating video content is employed in making movie trailers and advertising clips such as Synthesia, Maverick, etc.

Owing to the diversity of Generative-AI, which can serve as a learning aid amongst students, adopting AI in higher education is a topic of increasing interest and relevance. AI technologies, including Generative-AI, have the potential to revolutionise the way education is delivered, making it more personalised, efficient, and effective for learning in higher education (Lim et al., 2023; Sandu and Gide, 2019). Some studies adopted Generative-AI as a tool with constructivism learning theory, such as knowledge co-creation and collaborative learning (Salinas-Navarro et al, 2024, Zhou and Schofield, 2024)

One of the key factors influencing the adoption of AI in higher education is the technology's perceived usefulness and ease of use. This is consistent with the Technology Acceptance Model (TAM), which posits that these two factors significantly influence the intention to use technology (Davis, 1989). In the context of AI in education, perceived usefulness could be related to the potential of AI to enhance teaching and learning, while ease of use could be associated with the user-friendliness of the AI system (Lim et al., 2023).

Therefore, the integration of Generative-AI entails a process of endorsement through which an individual's behaviour demonstrates acceptance and engagement. The utilisation and cognitive development behaviours associated with Artificial Intelligence as an educational instrument enhance the efficacy of learning, facilitating the production of informational and media data, thereby improving educational outcomes (Kelly et al., 2023; Li, 2023; Pillai et al., 2023).

2.2 Technology Acceptance Model

To explore the receptivity and application of Generative-AI technologies amongst Thai higher education students, this investigation employs the Technology Acceptance Model (TAM) proposed by Davis (1989). This model provides a comprehensive theoretical framework for understanding the adoption and acceptance of technologies within information systems domains. In several years, the TAM has developed into an authoritative model elucidating the acceptance, refusal, and use of innovative technologies across diverse disciplines, including digital learning, information and communication technologies, and educational technology (Khlaisang, Teo, and Huang, 2019, Liu G et al., 2022, Ma and Huo, 2023)

The Technology Acceptance Model (TAM), as proposed by Davis (1989), suggests that users' acceptance and adoption of technology can be anticipated through their Behavioural Intention (BI) to use it. Behavioural intention refers to a person's belief in an action or behaviour that is about to happen in the future by predicting the outcome or impact of that action). BI can be measured using three types of questions: expect, want, and intend (Chuenphitthayavut, Zihuang and Zhu, 2020). BI can positively or negatively impact yourself or others, provided sufficient resources about user attitudes and subjective norms are provided for that action. Attitude has a significant positive effect on the intention to use AI. Personal concerns significantly negatively affect the intention to use AI (Cao et al., 2021).

In the TAM framework, BI is influenced by users' Perceived Usefulness (PU) of the technology in accomplishing specific tasks and the Perceived ease of use (PEOU) with which they can employ the technology. PU refers to an individual's awareness that technology can help improve learning performance. The awareness of its usefulness influences the choice and use of technology in learning. Including attitudes that affect acceptance and demonstrate a willingness to increase learning efficiency (Dhingra and Mudgal, 2019; Nugroho, Dewanti and Novitasari, 2018). Then, PEOU means "the degree to which a person believes using a particular system will be effortless." Rosenberg (1983) stated that many people's acceptance of technology depends on their use and learning to use it themselves. Learning how to use technology for people in society will result in continuously developing and improving technology. Sallam et al. (2023) state that perceived ease of use is the user's expectation that technology can be used quickly and effortlessly. The technology must be easily recognisable and have no complexity.

Moreover, PU and PEOU are influenced by Expected Benefits (EB), which means the degree to which students believe that AI applications improve the quality of learning and education. AI provides many ready-made programmes for self-learning or teacher-assisted learning (Al Darayseh, 2023; Nazaretsky, Cukurova, and Alexandron, 2022).

The model's attitudinal variables address Attitudes toward using (AT) or their BI towards technology use, typically quantified through the Intention to Use as a marker of attitudinal readiness towards embracing specific technologies (Davis, 1989; Venkatesh, 2000). According to Kim et al. (2020), technology is believed to be beneficial for users and easy to use, with a cheerful outlook towards its usage. In this study, the attitude toward using artificial intelligence consists of the perception that AI is easy to use and valuable. The positive or negative feelings of an individual towards the use of cognitive artificial intelligence in the educational process (Al-Adwan et al., 2023; Chatterjee and Bhattacharjee, 2020; Chou et al., 2022; Cruz-Benito et al., 2019; Sing et al., 2022).

Then, the foundational TAM elements in this research consist of EB, PEOU, PU, AT, BI, and AU. These components underscore a progression from cognitive recognition through attitudinal response to Actual use (AU) (Al-Emran, Mezhuyev, and Kamaludin, 2018; Davis, 1989). Furthermore, TAM encourages the exploration of AU patterns, thereby connecting theoretical constructs with practical observations. As Davis (1989) elucidates, the perceived user-friendliness of an application significantly enhances its perceived utility, thereby increasing the likelihood of its acceptance and adoption by individuals.

This study aims to investigate the application of Generative-AI technologies by Thai higher education students. The conceptualisations of the primary variables within the Technology Acceptance Model (TAM) have been refined and adopted. Hence, we set the operational definition in TAM for this study as follows in the Table 1.

Table 1: Definitions of main TAM components in this study

TAM components	**Definitions**
Expected Benefits (EB)	The degree to which students anticipate significant improvements in their learning outcomes because of integrating Generative-AI technologies into their learning.
Perceived Usefulness (PU)	The degree to which students are convinced that using Generative-AI technologies will significantly contribute to their learning.
Perceived Ease of Use (PEOU)	The degree to which students perceive that employing Generative-AI technologies will necessitate minimal exertion.
Attitude Toward Using (AT)	The degree of students' favourable or unfavourable evaluation regarding adopting Generative-AI technologies in their learning process.
Behavioural Intention (BI)	The degree of preparedness amongst learners to incorporate Generative-AI technologies into their educational endeavours.
Actual Use (AU)	The degree to which students effectively employ Generative-AI technologies within their educational context.

Hence, to clarify the hypothesised relationships between factors in the quantitative component of our study, we have introduced a structural model depicted in Figure 1. This model is grounded in the Technology Acceptance Model (TAM) and research hypotheses:

H1: EB positively influences PU of Generative-AI amongst higher education students.

H2: EB positively influences PEOU of Generative-AI amongst higher education students.

H3: PEOU positively influences PU of Generative-AI amongst higher education students.

H4: PEOU positively influences AT towards Generative-AI amongst higher education students.

H5: PU positively influences AT towards Generative-AI amongst higher education students.

H6: AT positively influences BI to use Generative-AI amongst higher education students.

H7: BI positively influences the AU of Generative-AI amongst higher education students.

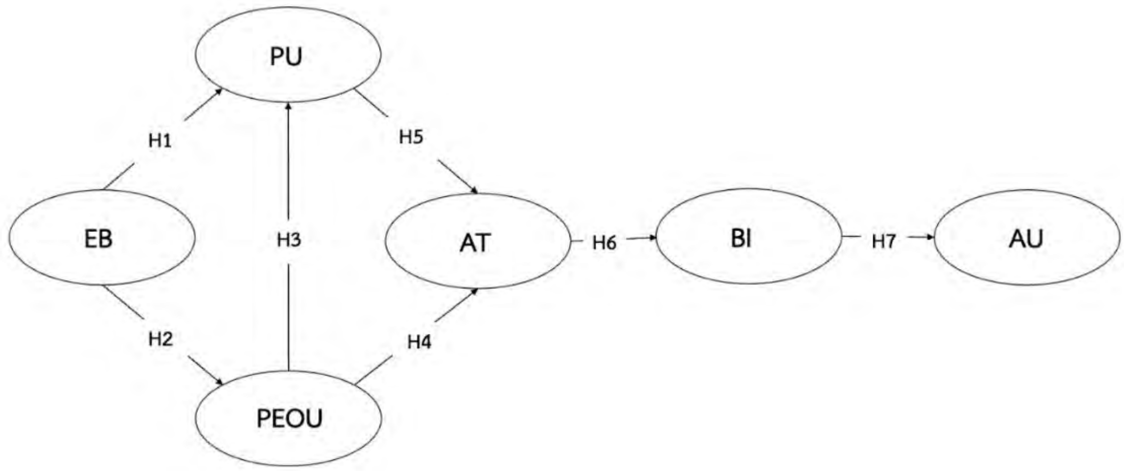

Figure 1: Research model of study

3. Research Methodology

3.1 Samples

In this research, the sample consisted of 911 students from 10 different Thai Universities Health Sciences, Sciences and Technology, Social Sciences and Humanities, and Vocational Fields, diversified in terms of academic level, gender, and field of study. The convenience random sampling method was used to distribute research instrument to samples for this study in each Thai Universities. Hair et al. (2018) suggested that the sample size was 10–20 samples per item for applying structural equation modelling (SEM). The current sample size of 911 with 6 constructs of 31 items was also considered fit and above (911 > 31*20 = 620) the desired level. Therefore, the sample size was considered appropriate to conduct SEM.

The researchers followed the privacy, data protection, and confidentiality policies. Therefore, all research participants' identities and data remained unidentifiable and will be deleted immediately after the research is completed. The data were consented by all participants for research purpose.

3.2 The Instrument

The research instrument, the survey questionnaire, was designed to gather data for the study and was divided into three parts. Part 1 focused on collecting demographic information from the sample, including gender, age, education levels, department, and year of study. This information is essential for understanding the characteristics and composition of the participants. Part 2 of the questionnaire aimed to gather information about the student's daily use and access to Generative-AI. This section explored the frequency and extent students engage with Generative-AI in their educational activities. Understanding students' current usage patterns provides insights into their familiarity with and exposure to Generative-AI. Part 3 of the questionnaire explored the students' perceptions and acceptance of Generative-AI. This section consisted of 31 items that assessed various dimensions of Technology Acceptance. Specifically, there were 5 items for EB, 6 items for PU, 5 items for PEOU, 5 items for AT, 5 items for BI, and 5 items for AU. Participants were asked to rate their agreement with each item on a 7-Likert scale ranging from "totally disagree" (1) to " totally agree" (7).

The evaluation of the quality of the Generative-AI Technology Acceptance Model (TAM) tool begins with establishing content validity through an extensive literature review. The researchers invited five subject matter experts in educational technology and artificial intelligence applications to assess the content validity of the measurement items about the study objectives. Regarding construct validity assessment, Confirmatory Factor Analysis (CFA) was conducted to examine the data's alignment with the hypothesized measurement model and the distinctiveness of the constructs. Adequate factor loadings and satisfactory fit indices indicate strong construct validity. Reliability analysis was performed by calculating Cronbach's alpha (CA) coefficients for each construct, which helped verify the internal consistency of the items, with values above 0.7 considered acceptable (Collier, 2020). The CA as internal consistency reliability values obtained from the data analysis for each construct were as follows: Expected Benefits = 0.88, Perceived Usefulness = 0.86, Perceived Ease of Use = 0.84, Attitude Toward Using = 0.81, Behavioural Intention = 0.86, and Actual Use = 0.78. These values were acceptable, indicating the reliability of the measurement items. Consequently, the researchers considered revising the wording of these items to enhance clarity and further distinguish them from other constructs.

Then, the researchers conducted a pilot test of the measurement instrument with a sample of 30 students to verify the clarity of the items and make appropriate adjustments to align with the context of higher education students in Thailand. This pilot testing with a representative sample of the target population enabled identifying and rectifying issues related to item clarity, response patterns, or scale reliability and validity. This iterative refinement process was crucial in enhancing the quality and applicability of the tool in assessing the acceptance of Generative-AI technologies, ensuring it effectively captures the nuances of this technology. The researcher initiated the research in March 2023. Following this, the research instrument was implemented from early May 2023 to mid-June 2023. By the end of June 2023, all data had been collected, cleaned, and analysed.

3.3 Data Analysis

The proposed research model underwent statistical analysis using SPSS V.29 and LISREL V.8.72 software. The analysis consisted of two stages. In the first stage, Confirmatory Factor Analysis (CFA) was conducted to assess the reliability and validity of the measurement model by examining the relationships between items and constructs. This study utilized several Goodness-of-Fit (GFI), including the Normed Fit Index (NFI), Comparative Fit Index (CFI), Adjusted Goodness-of-Fit Index (AGFI), and Root Mean Square Error of Approximation (RMSEA). Structural Equation Modelling literature suggests that a model demonstrates an excellent fit when NFI, CFI, GFI, and AGFI values exceed 0.95. For RMSEA, values below 0.05 indicate an excellent fit, while values below 0.08 are considered acceptable (Hair et al., 2018). The second stage involved evaluating the structural model, which included assessing the model fit, examining the research hypotheses, and exploring potential moderator effects. These analyses provide insights into the relationships and significance of the variables in the research model.

4. Result and Findings

4.1 Demographic of Samples

The study participants in Table 2 included 911 respondents, 558 females (61.3%) and 353 males (38.7%). The education level, most of the group are 806 bachelor's degree students (88.5%), followed by 65 master’s degree students (7.1%), 24 Doctoral degree students (2.6%), and 16 Diploma students (1.8%). Participants were affiliated with various academic departments; the highest group of samples from the Science and Technology department had 483 participants (53.0%). The Social Science and Humanities department had 236 participants (25.9%), while the Healthy Sciences department had 168 participants (18.4%). A smaller number of participants were from the Diploma programme, with 24 participants (2.6%). The average sample age is 21.61 (SD=4.63), the minimum age is 18, and the maximum is 59. The respondents are students in various years; there are 244 freshers (26.8%), 289 sophomores (31.7%), 245 juniors (26.9%), 117 seniors (12.8%), 13 5th-year students (1.4%), and 3 6^{th} year students (0.3%). However, participants who are Generative-AI user has 833 participants (91.4%), and 78 participants are non-Generative-AI users (8.6%).

Table 2: Overall demographic characteristics

Topics	Items	Frequency	%
Gender	Female	558	61.30
	Male	353	38.70
Education Level	Bachelor’s degree	806	88.50
	Master’s degree	65	7.10
	Doctoral Degree	24	2.60
	Diploma	16	1.80
Department	Science and Technology	483	53.00
	Social Science and Humanities	236	25.90
	Healthy Sciences	168	18.40
	Diploma	24	2.60

Topics	Items	Frequency	%
Year of Study	1st	244	26.80
	2nd	289	31.70
	3rd	245	26.90
	4th	117	12.80
	5th	13	1.40
	6th	3	0.30
Using Generative-AI	Yes	833	91.40
	No	78	8.60

Table 3 shows that 445 participants (53%) were not members of relevant professional organisations or associations, while 388 participants (47%) paid for membership registration. Regarding the type of Generative-AI utilised, the most common category was text Generative (f=435, 47.7%), followed by code Generative (f=240, 26.3%), Image Generative (f=108, 11.9%), sound Generative (f=13, 1.4%), and VDO Generative (f=37, 4.1%). Furthermore, participants reported varying frequencies of using Generative-AI in their educational activities. The most frequent use was "More than 1 time per day" (f=247, 27.1%), followed by "1 time a week" (f=234, 25.7%), "1 time a day" (f=212, 23.3%), "1 time bi-weekly" (f=78, 8.6%), and "1 time a month" (f=62, 6.8%). Regarding the time spent using Generative-AI, most participants (f=323, 35.5%) reported spending 2-4 hours on Generative-AI activities. Other time ranges included 1-2 hours (f=232, 25.5%), 4–7 hours (f=137, 15.0%), less than 1 hour (f=88, 9.7%), and more than 7 hours (f=53, 5.8%). Participants identified numerous benefits derived from using Generative-AI in education. The most reported benefit was "Seeking information" (f=601, 50.89%), followed by "Doing Task/Assignment" (f=208, 17.61%), "Being Pals" (f=172, 14.56%), "Exchanging Ideas" (f=116, 9.82%), and "Entertainment" (f=84, 7.11%). Participants indicated various sources of reference when using Generative-AI. Most participants (f=590, 52.26%) referred to Social Media platforms for information. Friends/Acquaintances were another commonly mentioned source, with 297 participants (26.31%) relying on them. TV served as a reference for 116 participants (10.27%), while Online Video Platforms were used by 126 participants (11.16%).

Table 3: Generative-AI users' behaviour

Topics	Items	Frequency	%
Member of Generative-AI services	Not Member	445	53.00
	Member	388	47.00
Type of Generative-AI	Text Generative	435	47.70
	Code Generative	240	26.30
	Image Generative	108	11.90
	Sound Generative	13	1.40
	Video Generative	37	4.10
Frequency of Use	More than 1 times per day	247	27.10
	One time a week	234	25.70
	One time a day	212	23.30
	One time for bi-weekly	78	8.60
	One time a month	62	6.80
Time to use	2-4 hrs.	323	35.50
	1-2 hrs.	232	25.50
	4-7 hrs.	137	15.00
	Less than 1 hr.	88	9.70
	more than 7 hours	53	5.80
Perceived benefits	Seeking information	601	50.89
	Doing Task/ Assignment	208	17.61

Topics	Items	Frequency	%
	Being Pals	172	14.56
	Exchanging Ideas	116	9.82
	Entertainment	84	7.11
Sources of reference	Social media	590	52.26
	Friends /Acquaintance	297	26.31
	TV	116	10.27
	Online Video Platform	126	11.16

4.2 Measurement Model

In the assessment of our measurement model, the constructs demonstrated varying degrees of fit. Attitude Toward Using technology (AT) showed a satisfactory fit with a Chi-Square of 7.49 (df=5), an RMSEA of 0.092, and good fit indices including CFI=0.97, NFI=0.94, and GFI=0.95. The Perceived Ease of Use (PEOU) and Behavioural Intention (BI) constructs also indicated good model fits, with PEOU recording a Chi-Square of 9.23, RMSEA of 0.120, and CFI of 0.97, and BI showing a Chi-Square of 8.08, RMSEA of 0.102, and CFI of 0.98. However, the Actual Use (AU) construct exhibited a less satisfactory fit, with a higher Chi-Square value of 13.38, RMSEA of 0.169, and lower fit indices such as CFI=0.93 and NFI=0.90. The Expected Benefits (EB) construct showcased the best model fit across all constructs with a Chi-Square of 3.90, RMSEA of 0.000, and perfect or near-perfect fit indices including CFI=1.00 and NFI=0.98. Perceived Usefulness (PU) showed a moderate fit, with a higher Chi-Square of 19.50, RMSEA of 0.130, and fit indices like CFI=0.96 and NFI=0.93.

In the Confirmatory Factor Analysis (CFA) results, the Kaiser-Meyer-Olkin (KMO) measure and Bartlett's test of sphericity are applied to assess the multivariate normality and the sufficiency of the sample. The significant result of Bartlett's sphericity test ($p < 0.01$), along with a KMO measure of 0.971, both exceeding the threshold of 0.60 (Tabachnick and Fidell, 2019), validated the suitability of the data for factor analysis. Tabachnick and Fidell (2019) also recommended that the univariate skewness should be under 2, and univariate kurtosis should be less than 4 for normal distribution. Despite the skewness values of all items below 2, only item AU1 exhibited kurtosis values exceeding 4. As per existing literature, the minimal acceptable value for CA was determined to be 0.60, and factor loadings should be above 0.60 (Hair et al., 2018).

Table 4 shows convergent and divergent validity were accessed via CFA on the measurement model, which shows that CA and Composite Reliability (CR) tests were performed to assess reliability. CA was applied to measure the internal consistency amongst items as seen in Table 5, while CR was used to describe the extent to which a train of items can represent potential constructs. The values ranged from 0.84 to 0.87, the CR values ranged from 0.44 to 0.90, the Factor Loading (FL) ranged from 0.46 to 0.9, and finally, the values of the Average Validity Extracted (AVE) of variables ranged from 0.52 to 0.90. Fornell and Larcker (1981) suggested that if AVE is less than 0.50 but CR is higher than 0.60, the convergent validity of the construct is still satisfactory.

Table 4: Descriptive statistics and measurement model

Construct	Items	Questions	M	SD	SK	KU	FL	α	CR	AVE
EB	EB1	Do you think artificial intelligence can help assess complex tasks and suggest real-time personalised recommendations for you?	6.08	0.91	-1.34	3.65	0.52	0.88	0.64	0.90
	EB2	Do you think that know-how artificial intelligence will help create smart agents? (Robot or software) to function as a learning partner or teaching assistant in learning?	5.98	0.95	-1.35	3.71	0.86			
	EB3	Do you think using artificial intelligence will help you plan or perform the assignments from teachers with quality?	5.95	0.86	-0.86	2.31	0.83			
	EB4	Do you think using artificial intelligence will increase your chances of improving your academic performance?	5.99	0.92	-0.89	1.77	0.84			
	EB5	Do you think that using artificial intelligence can help classmates see your existing learning abilities?	5.92	1.06	-1.38	3.16	0.90			

Construct	Items	Questions	M	SD	SK	KU	FL	α	CR	AVE
PU	PU1	Do you think that using know-how artificial intelligence makes learning activities easier?	6.11	0.84	-0.85	1.15	0.81	0.86	0.90	0.58
	PU2	Do you think that using know-how artificial intelligence helps you learn quickly?	6.03	0.86	-0.90	1.56	0.71			
	PU3	Do you think that using artificial intelligence will benefit your learning?	6.04	0.83	-0.68	0.57	0.74			
	PU4	Do you think that using knowledgeable artificial intelligence to help with your assignments?	6.00	0.90	-0.70	0.58	0.78			
	PU5	Do you think using cognitive artificial intelligence enhances your learning efficiency?	6.01	0.91	-1.06	2.56	0.60			
	PU6	Do you think that using artificial intelligence that you can create will make you more knowledgeable?	5.99	0.89	-0.75	1.05	0.78			
PEOU	PEOU1	Do you think you can quickly learn about using know-how artificial intelligence?	6.09	0.91	-1.25	3.25	0.72	0.84	0.84	0.52
	PEOU2	Do you think that using know-how artificial intelligence does not require much effort?	5.93	0.97	-1.17	2.60	0.72			
	PEOU3	Do you think that using know-how artificial intelligence is simple?	5.95	0.97	-1.32	3.25	0.55			
	PEOU4	Do you think that you can use artificial intelligence without asking for help from others?	5.94	1.00	-1.30	3.41	0.75			
	PEOU5	Do you think that using know-how artificial intelligence is easy for you?	5.98	0.94	-0.88	1.10	0.81			
AT	AT1	Do you think that it is a good thing to use artificial intelligence?	6.11	0.84	-0.66	0.25	0.66	0.81	0.50	0.83
	AT2	Do you know how to use Artificial Intelligence to enhance your learning?	6.04	0.81	-0.62	0.64	0.72			
	AT3	Do you think cognitive Artificial Intelligence is valuable to your learning and education?	6.05	0.85	-0.81	1.42	0.88			
	AT4	Do you feel comfortable incorporating artificial intelligence into your learning?	5.96	0.88	-0.64	0.90	0.60			
	AT5	Do you think that know-how artificial intelligence makes work easier and faster?	6.05	0.86	-0.62	0.22	0.62			
BI	BI1	When encountering a problem, do you think you will use artificial intelligence before asking others?	5.86	1.20	-1.64	3.58	0.82	0.86	0.86	0.56
	BI2	Do you think that when you encounter a problem, you will only use artificial intelligence to help solve it?	5.67	1.38	-1.66	2.86	0.90			
	BI3	Do you think that artificial intelligence can solve problems better than humans?	5.74	1.19	-1.40	2.79	0.74			
	BI4	Do you think artificial intelligence knows how to create and solve problems? You can work as you want.	5.79	1.04	-1.01	1.95	0.71			
	BI5	Do you think you need artificial intelligence to be developed more responsive to your lifestyle?	6.00	0.88	-0.96	2.16	0.50			
AU	AU1	Do you think you always use artificial intelligence to create text, images, or videos?	5.86	1.09	-1.66	4.63	0.46	0.78	0.45	0.80
	AU2	Do you think that you are interested in using artificial intelligence in the future?	6.08	0.81	-0.65	0.66	0.85			
	AU3	Do you think you will use artificial intelligence to support learning every time?	5.97	0.95	-1.31	3.47	0.68			

Construct	Items	Questions	M	SD	SK	KU	FL	α	CR	AVE
	AU4	Do you think that you are willing to keep up to date with your knowledge-based artificial intelligence skills?	6.03	0.93	-0.78	0.81	0.64			
	AU5	Do you think that you are happy to use knowledgeable artificial intelligence to support learning?	5.97	0.90	-0.66	0.83	0.66			

Table 5: Inter-construct correlations

	AU	BI	AT	PU	PEOU	EB
AU	1.00					
BI	0.65	1.00				
AT	0.79	0.57	1.00			
PU	0.80	0.65	0.84	1.00		
PEOU	0.68	0.70	0.67	0.74	1.00	
EB	0.74	0.74	0.72	0.82	0.75	1.00

Note. Values on the diagonal represent Pearson's Correlation value.

4.3 Structural Model: Goodness of fit Statistics and Hypothesis Testing

First, the overall model fit was assessed using multiple fit criteria; seven Goodness-of-Fit indices were used, including Chi-Square/Degree of Freedom, Goodness-of-Fit index (GFI), Adjusted Goodness-of-Fit Index (AGFI), Normalised Fit Index (NFI), Non-Normalised Fit Index (NNFI), Comparative Fit Index (CFI), and Root Mean Square Residual (RMSR). The SEM analysis revealed that the goodness of fit statistics of the theoretical framework in Table 5 represented a good fit (Chi-Square=1183.14, df=401, $p < 0.000$, $\chi2$ /df=2.95, GFI=0.90, AGFI=0.90, NFI=0.98, NNFI=0.99, CFI=0.99, RMSEA=0.48, SRMR=0.045).

An assessment of the direct effects between the research constructs was performed, and the results were as follows: EB (β=1.15, t=7.46 and β=0.92, t=19.72) has a significant positive influence on PU and PEOU in Generative-AI. PU (β=0.99, t=11.11) showed significant effects on Attitude toward Generative-AI. AT (β=1.02, t=14.01) significantly positively affected Behavioural Intention. Then, BI (β=0.78, t=16.36, $p < 0.00$) is significant in determining the AU of adopting Generative-AI. However, PEOU has no significant positive effect PU (β= -0.18, t= -1.25) and AT toward (β=0.01, t=0.08) in Generative-AI. Thus, most hypotheses were supported, as shown in Table 6 and Figure 2.

Table 6: Structural Equation Modelling results of the proposed model

Hypothesis	Standardized Solution	t-value	Results
H1: EB → PU	1.15	7.46***	Supported
H2: EB → PEOU	0.92	18.72***	Supported
H3: PEOU → PU	-0.18	-1.25	Not Supported
H4: PEOU → AT	0.01	0.08	Not Supported
H5: PU → AT	0.99	11.11***	Supported
H6: AT → BI	1.02	14.01***	Supported
H7: BI → AU	0.99	16.10***	Supported

** $p < 0.01$. *** $p < 0.001$.

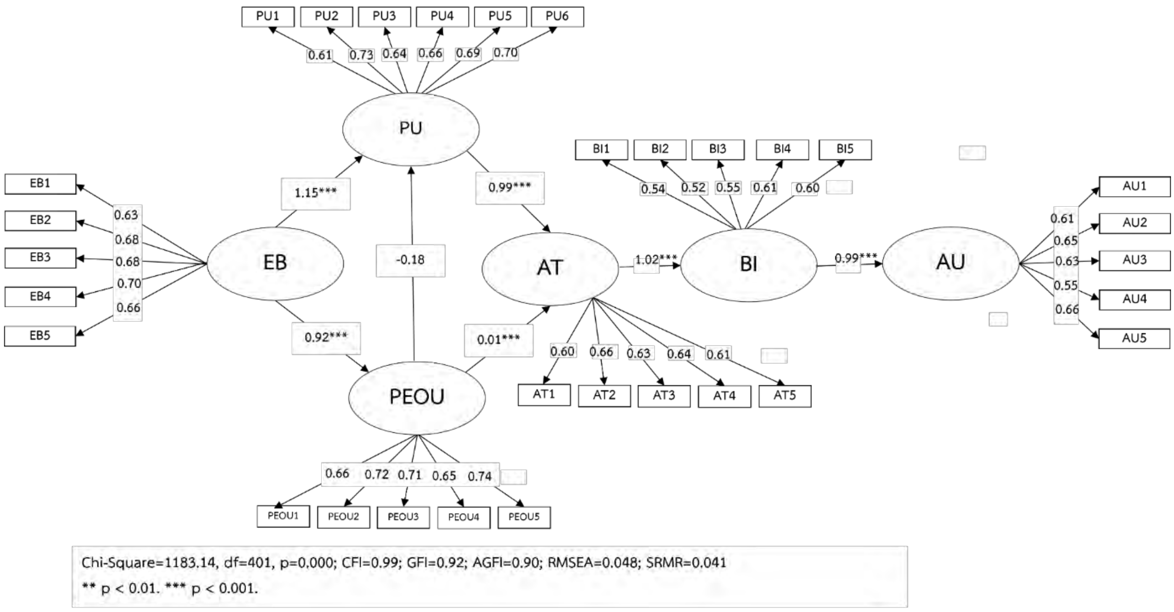

Figure 2: Result of Structural Equation Modelling

5. Discussion and Implications

The expeditious advancement of Generative-AI has the potential to revolutionise higher education, expanding new opportunities for personalised learning, knowledge discovery and transformation. This study contributes to the blooming body of research on AI adoption in education by investigation the factors influencing the acceptance of Generative-AI amongst Thai higher education students through the lens of the TAM.

One of the most captivating findings of this study is the negative relationship between Perceived Ease of Use (PEOU) and Perceived Usefulness (PU), challenging conventional assumptions of TAM (Venkatesh and Davis, 2000). Suggesting that as Generative-AI becomes more intuitive and user-friendly, students may paradoxically perceive it as less valuable for their learning. This could be attributed to the new generation of learners' emerging expectations and digital literacy. More sophisticated adaptive AI tools to keep pace with their learning needs (Ahmed et al., 2021; Keane et al., 2023). With continuous evolution and integration with other emerging technologies like virtual reality and brain-computer interfaces, AI-enable learning experiences that are not only easy to use but also cognitively challenging and emotionally engaging must be provided.

Another condemning implication of this study relates to the role of language proficiency in the even-handed access and adoption of Generative-AI in education. Whilst the current dominance of English in AI systems poses a barrier for non-native speakers (Bulathwela et al., 2021), the expeditious development of multilingual AI models and the increasing availability of municipal languages datasets offers promising solutions for bridging the language divergence. (Padmakumar, Stone and Mooney, 2018). Additionally, opportunities for creating immersive and personalised language acquisition experiences are presented by integrating Generative-AI in language learning as AI-powered language translation and generation become more accurate and contextually aware. Learners from diverse linguistic backgrounds can seamlessly collaborate and learn from each other using Generative-AI as a universal communication tool.

The crucial role of universities in promoting the use and innovative application of advanced content-creation technologies within the educational sector is underlined. Beyond solely consolidating these technologies into their syllabi, higher education institutions are encouraged to cultivate an environment conducive to innovation and experimentation. This involves motivating both students and faculty to collaborate on and explore new uses for these technologies across various academic fields (Chen, Chen and Lin, 2020; Sun et al., 2021). Achieving this goal requires a significant transformation in the educational approach, shifting from a traditional teacher-centric model to one that is centred around the learner. Learners are encouraged to take control of their educational journeys, using advanced tools for creative expression, knowledge searching, solving complex problems, and generating new knowledge.

Additionally, there is a call for the establishment of interdisciplinary research centres and hubs for innovation. These facilities would unite specialists from the fields of computer science, education, psychology, and others to examine the enduring effects of these technologies on learning processes, cognitive development, and societal interactions (Ng et al., 2022; UNESCO., 2023a).

However, the transformative possibility of Generative-AI in education also raises profound ethical and societal questions that cannot be ignored. As AI-generated content becomes increasingly sophisticated and indistinguishable from human-created works resulting in a risk of blurring the boundaries between originality, plagiarism, creativity, and automation (Su and Yang, 2023), educators and policymakers must proactively develop ethical frameworks and guidelines for the responsible use of Generative-AI in education to ensure that learners are well equipped with moral compass along with the critical thinking and knowledge creation skills (Wang et al., 2023). Moreover, the widespread adoption of Generative-AI in education may provoke existing inequalities and create new forms of digital divide, as learners from disadvantaged backgrounds may lack the access, skills, and support needed to leverage these technologies for their learning. These challenges will a concerted effort from all stakeholders, including educators, technology developers, civil society organisations and the governments to ensure an equitable access to Generative-AI in education and that no student is left behind (Ng et al., 2022).

In conclusion, this study provides a subtle understanding of the factors shaping the adoption of Generative-AI in Thai higher education. Embracing the opportunities and challenges of Generative-AI in education is a harness of its potential to create more engaging and personalised learning experiences for all learners while fostering the skills and values needed for responsible citizenship in AI-powered society.

6. Limitations and Future Studies

The present study provides valuable insights into the factors influencing the adoption of Generative-AI amongst learners of higher education in Thailand. Nevertheless, it is imperative to acknowledge the limitations and identify avenues for future research.

A primary limitation resides in the study's focus on a specific population: Thai learners enrolled in Thai universities. To enhance the understanding of Generative-AI adoption in education, future studies should encompass a more diverse sample, incorporating secondary students, teachers, and instructors from varied educational contexts and cultural backgrounds. This broader perspective would facilitate a more nuanced analysis of how different educational settings and user characteristics may influence the acceptance and utilisation of Generative-AI tools.

Another limitation of this study is its cross-sectional design, which collects data at a single point in time. Longitudinal studies would provide valuable insights into how user attitudes and behaviours towards Generative-AI in education evolve over time, given the rapid development in this field. Additionally, qualitative research methods, such as interviews and focus groups, could deepen our understanding of users' experiences, motivations, and challenges when interacting with Generative-AI technologies in educational contexts.

It is also imperative to acknowledge that this study focuses primarily on the Technology Acceptance Model (TAM) as its theoretical framework. While TAM offers a valuable lens for comprehending the key factors influencing technology adoption, future research could benefit from integrating additional theoretical perspectives, such as the Unified Theory of Acceptance and Use of Technology (UTAUT) or the Diffusion of Innovations Theory. These frameworks could assist in capturing a broader spectrum of individual, social, and contextual factors that shape the adoption and utilisation of Generative-AI in education.

Moreover, this research did not thoroughly examine the potential moderating effect of demographic variables, including gender, age, or academic discipline, on the interactions amongst the TAM constructs. Future research could investigate how these elements influence students' perceptions and behaviours regarding Generative-AI, offering a more intricate understanding of adoption patterns. It can also inform targeted interventions suitable for various user populations.

Lastly, in the context of Generative-AI in education, further research is necessary to explore the pedagogical implications and optimal strategies for integrating these tools into teaching and learning activities. Future studies could examine how Generative-AI can be effectively harnessed to facilitate various educational goals, such as personalised learning, collaborative problem-solving, and creative expression. Additionally, research on the ethical and societal aspects of Generative-AI in education, addressing concerns about privacy, bias, and intellectual property, is crucial. This will guide the responsible development and implementation of these technologies.

In conclusion, while this study contributes significantly to understanding Generative-AI adoption in Thai higher education, it also emphasises the necessity for more research to overcome its limitations and explore new directions. By building upon the findings of this study and expanding its scope, future research can contribute to unlocking the full potential of Generative-AI in education. It can also ensure the development and utilisation of these technologies in an equitable, ethical, and pedagogically sound manner.

Author Contributions

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All authors have read and agreed to the published version of the manuscript.

Disclosure statement

All authors declare that they have no conflict of interest.

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References

Ahmad, S. F., Rahmat, M. K., Mubarik, M. S., Alam, M. M., and Hyder, S. I., 2021. Artificial Intelligence and Its Role in Education. *Sustainability (Switzerland)*, *[e-journal] 13*(22). https://doi.org/10.3390/su132212902

Ahmed, Y. A., Mohamed, M. M., Ali, A. F., Alasso, M. M., Siyad, A. D., and Ahmad, M. N. 2021. Evaluating Students Perspectives on ICT Readiness in Somali Higher Education towards Teaching - Learning Acceptance. https://doi.org/abs/2108.11455

Al-Adwan, A. S., Li, N., Al-Adwan, A., Abbasi, G. A., Albelbis, N. A., and Habibi, A., 2023. Extending the Technology Acceptance Model (TAM) to Predict University Students' Intentions to Use Metaverse-Based Learning Platforms. *Education and Information Technologies*. [e-journal]. https://doi.org/10.1007/s10639-023-11816-3

Al-Emran, M., Mezhuyev, V., and Kamaludin, A. ,2018. Technology Acceptance Model in M-learning context: A systematic review*. Computers & Education*, [e-journal] 125, 389-412. https://doi.org/10.1016/j.compedu.2018.06.008

Al Darayseh, A., 2023. Acceptance of artificial intelligence in teaching science: Science teachers' perspective. *Computers and Education: Artificial Intelligence*, *[e-journal] 4*. https://doi.org/10.1016/j.caeai.2023.100132

Buddemeyer, A., Walker, E., and Alikhani, M., 2021. Words of Wisdom: Representational Harms in Learning From AI Communication. https://doi.org/10.48550/arXiv.2111.08581

Bulathwela, S., Pérez-Ortiz, M., Holloway, C., and Shawe-Taylor, J., 2021. Could AI Democratise Education? Socio-Technical Imaginaries of an EdTech Revolution. https://doi.org/10.48550/arXiv.2112.02034

Cao, G., Duan, Y., Edwards, J. S., and Dwivedi, Y. K., 2021. Understanding managers' attitudes and behavioral intentions towards using artificial intelligence for organizational decision-making. [e-journal] *Technovation*, *106*. https://doi.org/10.1016/j.technovation.2021.102312

Celik, I., Dindar, M., Muukkonen, H., and Järvelä, S., 2022. The Promises and Challenges of Artificial Intelligence for Teachers: a Systematic Review of Research. *TechTrends*, *[e-journal] 66*(4), pp.616-630. https://doi.org/10.1007/s11528-022-00715-y

Chan, C. K. Y., and Hu, W., 2023. Students' Voices on Generative AI: Perceptions, Benefits, and Challenges in Higher Education. *Computers and Society*. *[e-journal].* https://doi.org/10.48550/arXiv.2305.00290

Chatterjee, S., and Bhattacharjee, K. K., 2020. Adoption of artificial intelligence in higher education: a quantitative analysis using structural equation modelling. *Education and Information Technologies*, *[e-journal] 25*(5), pp.3443-3463. https://doi.org/10.1007/s10639-020-10159-7

Chen, L., Chen, P., and Lin, Z., 2020. Artificial Intelligence in Education: A Review. *IEEE Access*, *[e-journal] 8*, pp.75264-75278. https://doi.org/10.1109/ACCESS.2020.2988510

Chou, C.-M., Shen, T.-C., Shen, T.-C., and Shen, C.-H., 2022. Influencing factors on students' learning effectiveness of AI-based technology application: Mediation variable of the human-computer interaction experience. *Education and Information Technologies*, *[e-journal] 27*(6), pp.8723-8750. https://doi.org/10.1007/s10639-021-10866-9

Chuenphitthayavut, K., Zihuang, T., and Zhu, T., 2020. The prediction of behavioral intention to use online mental health interventions. *Psych J*, *[e-journal] 9*(3), pp.370-382. https://doi.org/10.1002/pchj.333

Collier JE., 2020. *Applied Structural Equation Modeling Using AMOS: Basic to Advanced Techniques*. 1st Ed. Abingdon, Oxon, UK: Routledge. 366 p.

Cooper, G., 2023. Examining Science Education in ChatGPT: An Exploratory Study of Generative Artificial Intelligence. *Journal of Science Education and Technology*, *[e-journal] 32*(3), pp.444-452. https://doi.org/10.1007/s10956-023-10039-y

Cruz-Benito, J., Sánchez-Prieto, J. C., Therón, R., and García-Peñalvo, F. J., 2019. Measuring Students' Acceptance to AI-Driven Assessment in eLearning: Proposing a First TAM-Based Research Model. In P. Zaphiris and A. Ioannou, *Learning and Collaboration Technologies. Designing Learning Experiences* Cham.

Dai, Y., Liu, A., and Lim, C. P., 2023. *Reconceptualizing ChatGPT as a student-driven innovation in higher education*. [pdf] Available at: https://doi.org/10.13140/RG.2.2.33039.05283

Davis, F., Bagozzi, R., and Warshaw, P., 2006. Extrinsic and Intrinsic Motivation to Use Computers in the Workplace. *Journal of Applied Social Psychology*, *[e-journal] 22*, pp.1111-1132. https://doi.org/10.1111/j.1559-1816.1992.tb00945.x

Davis, F. D., 1989. Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, *[e-journal] 13*, pp.319–340. https://doi.org/10.2307/249008

Dhingra, M., and Mudgal, R. K., 2019. Applications of Perceived Usefulness and Perceived Ease of Use: A Review. 2019 8th International Conference System Modeling and Advancement in Research Trends (SMART),

Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., Duan, Y., Dwivedi, R., Edwards, J., Eirug, A., Galanos, V., Ilavarasan, P. V., Janssen, M., Jones, P., Kar, A. K., Kizgin, H., Kronemann, B., Lal, B., Lucini, B., . . . Williams, M. D., 2021. Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management*, *[e-journal] 57*. https://doi.org/10.1016/j.ijinfomgt.2019.08.002

Fornell, C., and Larcker, D. F., 1981. Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. *Journal of Marketing Research*, *[e-journal] 18*(1), pp.39-50. https://doi.org/10.2307/3151312

Gimpel, H., Hall, K., Decker, S., Eymann, T., Lämmermann, L., Mädche, A., Röglinger, M., Ruiner, C., Schoch, M., Schoop, M., Urbach, N., and Vandirk, S., 2023. *Unlocking the Power of Generative AI Models and Systems such as GPT-4 and ChatGPT for Higher Education: A Guide for Students and Lecturers*. [pdf] Available at: https://digital.uni-hohenheim.de/fileadmin/einrichtungen/digital/Generative_AI_and_ChatGPT_in_Higher_Education.pdf

Gustafson, T., 2023. *Generative AI – What Could it Mean for Higher Education?* [online] Available at: https://teaching.nmc.edu/generative-ai-what-could-it-mean-for-higher-education/

Hair, J. F., Black, W. C., Babin, B. J., and Anderson, R. E., 2018. *Multivariate data analysis* (8th ed.). Cengage.

Hutson, J., Jeevanjee, T., Graaf, V. V., Lively, J., Weber, J., Weir, G., Arnone, K., Carnes, G., Vosevich, K., Plate, D., Leary, M., and Edele, S., 2022. Artificial Intelligence and the Disruption of Higher Education: Strategies for Integrations across Disciplines. *Creative Education*, *[e-journal] 13*(12), pp.3953–3980. https://doi.org/10.4236/ce.2022.1312253

Jiayang Wu, W. G., Zefeng Chen, Shicheng Wan, Hong Lin. (2023). AI-Generated Content (AIGC): A Survey. https://doi.org/arXiv:2304.06632v1

Kashive, N., Powale, L., and Kashive, K., 2021. Understanding user perception toward artificial intelligence (AI) enabled e-learning. *The International Journal of Information and Learning Technology*, *[e-journal] 38*(1), pp.1-19. https://doi.org/10.1108/IJILT-05-2020-0090

Keane, T., Linden, T., Hernandez-Martinez, P., Molnar, A., and Blicblau, A., 2023. Digital technologies: students' expectations and experiences during their transition from high school to university. *Education and Information Technologies*, *[e-journal] 28*(1), pp.857-877. https://doi.org/10.1007/s10639-022-11184-4

Kelly, S., Kaye, S.-A., and Oviedo-Trespalacios, O., 2023. What factors contribute to the acceptance of artificial intelligence? A systematic review. *Telematics and Informatics*, *[e-journal] 77*,. https://doi.org/10.1016/j.tele.2022.101925

Khlaisang, J., Teo, T., and Huang, F., 2019. Acceptance of a flipped smart application for learning: a study among Thai university students. *Interactive Learning Environments*, *[e-journal],* https://doi.org/10.1080/10494820.2019.1612447

Kim, J., Merrill, K., Xu, K., and Sellnow, D. D., 2020. My Teacher Is a Machine: Understanding Students' Perceptions of AI Teaching Assistants in Online Education. *International Journal of Human–Computer Interaction*, *[e-journal] 36*(20), pp.1902-1911. https://doi.org/10.1080/10447318.2020.1801227

Li, K., 2023. Determinants of College Students' Actual Use of AI-Based Systems: An Extension of the Technology Acceptance Model. *Sustainability (Switzerland)*, *[e-journal] 15*(6). https://www.mdpi.com/2071-1050/15/6/5221

Lim, W. M., Gunasekara, A., Pallant, J. L., Pallant, J. I., and Pechenkina, E., 2023. Generative AI and the future of education: Ragnarök or reformation? A paradoxical perspective from management educators [Article]. *International Journal of Management Education*, *[e-journal] 21*(2). https://doi.org/10.1016/j.ijme.2023.100790

Liu, G. L., Darvin, R., and Ma, C. ,2024. Exploring AI-mediated informal digital learning of English (AI-IDLE): a mixed-method investigation of Chinese EFL learners' AI adoption and experiences. Computer Assisted Language Learning, [e-journal], https://doi.org/10.1080/09588221.2024.2310288

Liu, S., Chen, Y., Huang, H., Xiao, L., and Hei, X., 2018. Towards Smart Educational Recommendations with Reinforcement Learning in Classroom. 2018 IEEE International Conference on Teaching, Assessment, and Learning for Engineering (TALE),

Ma, X., and Huo, Y. ,2023. Are users willing to embrace ChatGPT? Exploring the factors on the acceptance of chatbots from the perspective of AIDUA framework. *Technology in Society*, [e-journal] 75,. https://doi.org/10.1016/j.techsoc.2023.102362

Murugesan, S., and Cherukuri, A. K., 2023. The Rise of Generative Artificial Intelligence and Its Impact on Education: The Promises and Perils. *[e-journal] 56*(05), pp.116-121. https://doi.org/10.1109/mc.2023.3253292

Nazaretsky, T., Cukurova, M., and Alexandron, G., 2022. *An Instrument for Measuring Teachers' Trust in AI-Based Educational Technology* LAK22: 12th International Learning Analytics and Knowledge Conference, Online, USA. Ng, D. T. K., Leung, J. K. L., Su, M. J., Yim, I. H. Y., Qiao, M. S., and Chu, S. K. W. ,2022. *AI Literacy for All*. In AI Literacy in K-16 Classrooms (pp. 21-29). Springer International Publishing. https://doi.org/10.1007/978-3-031-18880-0_3

Ng, D. T. K., Leung, J. K. L., Su, M. J., Yim, I. H. Y., Qiao, M. S., and Chu, S. K. W. ,2022. *AI Education and AI Literacy*. In AI Literacy in K-16 Classrooms (pp. 9-19). Springer International Publishing. https://doi.org/10.1007/978-3-031-18880-0_2

Nguyen, N., 2023. *Opportunities and challenges of AI in higher education*. [online] Available at: https://feedbackfruits.com/blog/opportunities-and-challenges-of-ai-in-higher-education

Nugroho, M. A., Dewanti, P. W., and Novitasari, B. T., 2018. The Impact of Perceived Usefulness and Perceived Ease of Use on Student's Performance in Mandatory E-Learning Use. 2018 International Conference on Applied Information Technology and Innovation (ICAITI),

Padmakumar, A., Stone, P., and Mooney, R. J., 2018. Learning a Policy for Opportunistic Active Learning. [pdf] Available at: https://doi.org/10.48550/arXiv.1808.10009

Pillai, R., Sivathanu, B., Metri, B., and Kaushik, N., 2023. Students' adoption of AI-based teacher-bots (T-bots) for learning in higher education. *Information Technology & People*, *ahead-of-print*(ahead-of-print). , *[e-journal].* https://doi.org/10.1108/ITP-02-2021-0152

Qureshi, R., Shaughnessy, D., Gill, K. A. R., Robinson, K. A., Li, T., and Agai, E., 2023. Are ChatGPT and large language models "the answer" to bringing us closer to systematic review automation? *Systematic Reviews*, *[e-journal] 12*(1), pp.72. https://doi.org/10.1186/s13643-023-02243-z

Rasul, T., Nair, S., Kalendra, D., Robin, M., Santini, F., Ladeira, W., Sun, M., Day, I., Rather, A., and Heathcote, L., 2023. The role of ChatGPT in higher education: Benefits, challenges, and future research directions. *Journal of Applied Learning & Teaching*, , *[e-journal] 6*. https://doi.org/10.37074/jalt.2023.6.1.29

Rosenberg, N., 1983. *Inside the Black Box: Technology and Economics*. Cambridge University Press. [pdf] Available at: https://doi.org/10.1017/CBO9780511611940

Rudra, S., 2023. How Can Generative AI Be Used in Higher Ed?. [online] Available at: https://edtechmagazine.com/higher/article/2023/01/how-can-generative-ai-be-used-higher-ed

Sallam, M., Salim, N., Barakat, M., Al-Mahzoum, K., Al-Tammemi, A., Malaeb, D., Hallit, R., and Hallit, S., 2023. *Validation of a Technology Acceptance Model-Based Scale TAME-ChatGPT on Health Students Attitudes and Usage of ChatGPT in Jordan*. [pdf] Available at: https://doi.org/10.2196/preprints.48254

Salinas-Navarro, D. E., Vilalta-Perdomo, E., Michel-Villarreal, R., and Montesinos, L., 2024. Using Generative Artificial Intelligence Tools to Explain and Enhance Experiential Learning for Authentic Assessment. *Education Sciences*, *[e-journal]* 14(1), https://doi.org/10.3390/educsci14010083

Sandu, N., and Gide, E., 2019. Adoption of AI-Chatbots to Enhance Student Learning Experience in Higher Education in India. 2019 18th International Conference on Information Technology Based Higher Education and Training (ITHET),

Sing, C. C., Teo, T., Huang, F., Chiu, T. K. F., and Xing wei, W., 2022. Secondary school students' intentions to learn AI: testing moderation effects of readiness, social good and optimism. *Educational Technology Research and Development*, *[e-journal] 70*(3), pp.765-782. https://doi.org/10.1007/s11423-022-10111-1

Singh, S. V., and Hiran, K. K., 2022. The Impact of AI on Teaching and Learning in Higher Education Technology. *Journal of Higher Education Theory and Practice*, *[e-journal] 22*(13). https://doi.org/10.33423/jhetp.v22i13.5514

Song, N. ,2024. Higher education crisis: Academic misconduct with generative AI. *Journal of Contingencies and Crisis Management*, *[e-journal]* 32(1). https://doi.org/10.1111/1468-5973.12532

Su , J., and Yang , W., 2023. Unlocking the Power of ChatGPT: A Framework for Applying Generative AI in Education. *ECNU Review of Education*, *[e-journal] pp.*1-12. https://doi.org/10.1177/20965311231168423

Sun, Z., Anbarasan, M., and Praveen Kumar, D., 2021. Design of online intelligent English teaching platform based on artificial intelligence techniques. *Computational Intelligence*, *37*(3), 1166-1180. https://doi.org/https://doi.org/10.1111/coin.12351

Tabachnick, B., and Fidell, L., 2019. *Using Multivariate Statistics*. 7th ed. Pearson.

Toksha, B., Kulkarni, T., and Gupta, P., 2022. Impact of AI on Teaching Pedagogy and its Integration for Enhancing Teaching-Learning. [pdf] Available at: https://doi.org/10.1201/9781003184157-7

UNESCO., 2023a. *The challenges and opportunities of Artificial Intelligence in education*. [online] Available at: https://www.unesco.org/en/articles/challenges-and-opportunities-artificial-intelligence-education

UNESCO., 2023b. *Ministerial Roundtable on Generative AI in Education*. [online] Available at: https://www.unesco.org/en/articles/ministerial-roundtable-generative-ai-education

Venkatesh, V. ,2000,. Determinants of Perceived Ease of Use: Integrating Control, Intrinsic Motivation, and Emotion into the Technology Acceptance Model. Information Systems Research, [e-journal] 11(4), 342-365. http://www.jstor.org/stable/23011042

Venkatesh, V., and Davis, F. D., 2000. A Theoretical Extension of the Technology Acceptance Model: Four Longitudinal Field Studies. *Management Science*, *[e-journal] 46*(2), pp.186-204. https://doi.org/10.1287/mnsc.46.2.186.11926

Wang, X., Anwer, N., Dai, Y., and Liu, A., 2023. *ChatGPT for design, manufacturing, and education*. [pdf] Available at: https://doi.org/10.13140/RG.2.2.35077.22244

World Economic Forum., 2023. The Growth Summit: Jobs and Opportunity for All. [online] Available at: https://www.weforum.org/events/the-growth-summit-jobs-and-opportunity-for-all-2023

Yue, M., Jong, M. S.-Y., and Dai, Y., 2022. Pedagogical Design of K-12 Artificial Intelligence Education: A Systematic Review. *Sustainability (Switzerland)*, *[e-journal] 14*(23). https://www.mdpi.com/2071-1050/14/23/15620

Zawacki-Richter, O., Marín, V. I., Bond, M., and Gouverneur, F., 2019. Systematic review of research on artificial intelligence applications in higher education – where are the educators? *International Journal of Educational Technology in Higher Education*, *[e-journal] 16*(1), pp. 39. https://doi.org/10.1186/s41239-019-0171-0

Zhou, X., and Schofield, L., 2024. Using social learning theories to explore the role of generative Artificial Intelligence (AI) in collaborative learning. *Journal of Learning Development in Higher Education, [e-journal]* (30). https://doi.org/10.47408/jldhe.vi30.1031