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Integrating a Custom Chatbot Into Higher Education: From Passive to Interactive E-Learning

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ABSTRACT

Although e-learning is considered one of the leading teaching methods in higher education, both learners and instructors face significant challenges owing to reduced social interaction compared with traditional classroom learning. In this study, we explore the leveraging of recent developments in generative artificial intelligence (AI) and create a custom chatbot using retrieval-augmented generation. A research model combining the technology acceptance model and the interactive-constructive-active-passive theory was developed and used to investigate how the chatbot affects students' perceptions and perceived learning outcomes in online and blended classes. This study provides empirical evidence indicating that custom chatbots can be integrated into higher education to enhance students' e-learning experiences, and through interacting with chatbots, students' behaviors shift from passive to interactive engagement. The findings shed light on how generative AI helps to improve e-learning experience, highlighting the effectiveness of such technology in support of social interaction and emotional engagement in higher education. The study also demonstrates the feasibility of deploying custom AI chatbots in college classes and provides practical recommendations.

Keywords: Chatbot, e-Learning, Generative AI in teaching, Higher education, Online learning

1. INTRODUCTION

A chatbot is an artificial intelligence (AI) system that employs anthropomorphic design to simulate human-like interaction with users. There have been growing applications of chatbots in business and research communities to streamline processes and increase operational efficiency (Adamopoulou & Moussiades, 2020). With the recent revolutionary development of generative AI and large language models (LLMs), such as OpenAI's ChatGPT, Google's Gemini, and DeepSeek, chatbots present many opportunities for developing new applications in areas besides e-learning, such as customer service, mental healthcare, and content generation (Zhong & Kim, 2024).

When used interchangeably, e-learning or online learning can be broadly defined as the bridge between teachers and students through the use of web-based technologies (Miller et al., 2017). In a narrower sense, e-learning is a type of learning environment where learners interact with technological platforms and engage in self-directed and independent learning (Santhanam et al., 2008). In this study, we adopt the broad definition of e-learning and use it interchangeably with online learning and online education (Singh & Thurman, 2019).

E-learning has gained significant popularity in the last two decades because of its potential to provide flexible access to content and instruction at any time and from anywhere (Castro & Tumibay, 2021). According to the National Center for Education Statistics (n.d.), 61% of college students in the United States had taken at least one class online in the fall of 2021, and 28% of undergraduate students took online classes exclusively in 2021. Online classes are classes that use the Internet in some way to facilitate or enhance the interaction between instructors and students (Curtain, 2002). In online classes, instructional delivery and interaction may be supported by asynchronous communication tools (e.g., email, discussion boards, learning platforms), synchronous technologies (e.g., videoconferencing tools, chatrooms), or a combination of asynchronous and synchronous forms. Another recent trend in higher education is offering classes partially online and partially face-to-face, which is referred to as blended learning (Jackson & Helms, 2008). Blended classes integrate e-learning with traditional classroom instruction, providing potential benefits, such as increased flexibility, resources for learning, and leverage of instructional technology (Tayebinik & Puteh, 2013). Despite the popularity of e-learning, both learners and instructors face challenges owing to reduced social interaction compared with traditional classroom learning (Wragg, 2019). Previous studies suggest that the lack of support and reduced engagement are the major obstacles to effective e-learning (Crockett et al., 2017; Essel et al., 2022).

In this research, we explored how recent developments in generative AI can be leveraged to enhance e-learning. We created and tested a custom AI chatbot powered by a transformer-based deep learning model (OpenAI's GPT-4) in four asynchronous online and one blended undergraduate business classes. We equipped the chatbot with advanced natural language processing (NLP) and understanding capabilities that can potentially help to improve student engagement, learner-content interaction, and perceived learning outcomes. The chatbot acts as a virtual assistant that helps students locate course materials and answers general course-related questions as well as specific questions about assignments and projects. As a pretrained augmented model, it can also answer subject-related questions and directs students to various resources as needed.

This research contributes to the growing community of online education, enriches existing literature on technology-enhanced e-learning, and adds to innovative pedagogical practices. Specifically, it makes the following theoretical and pedagogical contributions.

First, this study extends the literature on e-learning with an empirically evaluated framework that integrates the technology acceptance model (TAM) and the interactive-constructive-active-passive (ICAP) theory. TAM, along with its many versions, is a leading theoretical model for assessing technological deployments in different educational contexts, including e-learning (Gong et al., 2004; Granić & Marangunić, 2019). ICAP is a well-established theory about the processes of how students learn through their physical and cognitive behaviors (Chi & Wylie, 2014). Combining the two models in this study, we shed light on how a custom chatbot can help improve learning experience and perceived learning outcomes, highlighting the effectiveness of AI in support of social interaction and emotional engagement.

Second, we provide recommendations from a practical perspective for designing and implementing generative AI in higher education. For educators who are interested in incorporating similar technologies in their own courses, we included in this paper details of the development, such as the system components, technological platform, costs, development time, and alternative options.

This paper is organized as follows. In the next section, we review related work and develop a research framework. We then present the research design followed by data analysis and results. We also discuss the findings, implications, and limitations of this study and then share our conclusion.

2. THEORETICAL FOUNDATIONS

2.1 Chatbots for Higher Education

Since its introduction by OpenAI, ChatGPT has received significant public attention and started an intense debate among educators, students, and practitioners on the transformative effects of AI-based chatbots on education. ChatGPT is an anthropomorphic AI system that can answer a wide variety of questions in human-like dialogues. According to an article on the ChatGPT website (OpenAI, 2022), "the dialogue format makes it possible for ChatGPT to answer follow-up questions, admit its mistakes, challenge incorrect premises, and reject inappropriate requests." Based on advanced deep learning algorithms and NLP techniques, ChatGPT can generate human-like answers to user queries that are coherent, orderly, and informative (Hien et al., 2018; Zhong & Kim, 2024). Despite the concerns for potential misuse of AI-generated content that may jeopardize the integrity and fairness of academic assessments, educational institutions can benefit from using AI chatbots to support instructional design, inclusive learning, personalized learning, and online education (Bilquise et al., 2024; Gupta & Chen, 2022).

Although ChatGPT is a relatively new platform, chatbot technology has been studied and integrated into education for many years. As early as in the 1990s, chatbots were developed to moderate online chatrooms. These bots looked for certain text patterns submitted by chatroom participants and reacted with automated actions (Ait Baha et al., 2024; Colace et al., 2018). Farhan et al. (2012) designed a chatbot using the Pandorabot platform (https://home.pandorabots.com), an online chatbot development and hosting service. This web-based chatbot stored questions and answers in an XML-style format and automatically replied to students' queries in e-learning environments. Nenkov et al. (2016) proposed an intelligent agent in the form of a chatbot to automate the interaction between a student and a teacher within the framework of the Moodle learning management system. The chatbot was developed using the IBM Watson platform and implemented through Facebook Messenger. In addition, researchers have created chatbot-based learning systems to provide learning support and tutoring services to university students in computer science and programming courses (Colace et al., 2018; Hobert, 2019). Previous researchers also studied chatbots that can generate quizzes or interview questions based on built-in knowledge. For example, Sreelakshmi et al. (2019) proposed a question-answering and quiz-generation chatbot that took an uploaded pdf document as input and enabled students to ask questions from the text or request quiz questions. Gupta and Chen (2022) developed an interview chatbot using Juji Studio, a commercial platform for building custom chatbots. The chatbot was used as an experimental platform to investigate the design opportunities of using chatbots for inclusive learning.

Prior research has mainly focused on implementing chatbots that help to improve skill development, efficiency of education, students' motivation, and availability of education (Wollny et al., 2021). Most of these chatbots were developed using NLP, machine learning, and domain ontologies. Despite extensive research efforts, the application and use of chatbots in education have been limited owing to the difficulties of overcoming several key challenges, including the NLP lexical gap, context awareness, and linguistic ambiguity (Chen et al., 2020; Fryer et al., 2017; Savin-Baden et al., 2015). To fill this gap, in this study we focused on custom chatbots empowered by cutting-edge technologies to provide one-on-one educational support to business students. We aimed to investigate the opportunities and effectiveness of using the chatbot to improve student engagement and assess user acceptance of generative AI in online and blended classes where students spend a significant amount of time interacting with e-learning systems (Santhanam et al., 2008).

Table 1 shows the representative publications related to chatbot applications in higher education from 2015 to 2024.

2.2 Technology Acceptance Model (TAM)

TAM was developed to elucidate the factors influencing users' adoption of emerging information technologies and associated applications (Davis, 1989). According to the TAM, two core beliefs—perceived ease of use and perceived usefulness—serve as principal determinants in shaping users' dispositions toward embracing a novel technology and their attitudes toward using it (Davis et al., 1989). Perceived ease of use refers to individuals' convictions that using a new technology will entail minimal effort. Perceived usefulness denotes individuals' subjective assessment of the likelihood that employing new technology will enhance their attitudes toward using it. According to existing literature, perceived usefulness emerges as a robust precursor elucidating students' attitudes toward employing chatbots (Al-Abdullatif, 2023) and their intentions to adopt chatbot technology (Bilquise et al., 2024; Chen et al., 2020). Previous studies suggested that researchers attempted to develop effective chatbots that can understand the context of students' queries, emulate human dialogs, create social support, and provide accurate and timely answers (Liu et al., 2022; Rapp et al., 2021). Consequently, TAM has been used as a preeminent framework for investigating the decision-making process behind students' adoption and acceptance of specific learning technologies related to generative AI (Saif et al., 2024). Thus, we hypothesize that when students perceive the chatbot as an easy-to-use, useful tool that can effectively facilitate their academic tasks, they are more likely to develop a positive attitude toward using it. Basing our focus on the TAM, we propose our first three hypotheses:

- H1a: Students' perceived ease of use of the chatbot has a positive relationship with their perceived usefulness of it.
- H1b: Students' perceived ease of use of the chatbot has a positive relationship with their attitudes toward using it.
- H1c: Students' perceived usefulness of the chatbot has a positive relationship with their attitudes toward using it.

2.3 Interactive-Constructive-Active-Passive (ICAP)

The ICAP framework (Chi & Wylie, 2014), designed to enhance students' learning experiences from the pedagogy and curriculum design perspective, has become a popular model guiding course design in higher education. In this model, four modes of learning activities are defined based on students' engagement behaviors: interactive, constructive, active, and passive (Chi, 2009). These learning modes are commonly used in the cognitive science of learning to describe and assess learners' activities. In the passive mode, a student receives information from the instructional materials without doing anything else related to learning. When a form of action or manipulation (e.g., repeating, copying, highlighting) is undertaken, the student is engaged in active learning. If the student produces additional output (e.g., taking notes or asking questions in their own words) beyond what is given in the learning materials, then they exhibit constructive behaviors. In the interactive mode, the student engages in conversation with a partner who can be a fellow student, a teacher, or a computer agent. It is worth noting that interactive activities are likely to be better than the other three modes (Chi & Wylie, 2014).

In education, students' attitudes toward using chatbots have been well examined (Fryer et al., 2017). The educational sphere consistently embraces the integration of innovative technologies to enhance students' interaction and engagement (Granić & Marangunić, 2019). Hobert (2019) suggested that students' attitudes toward using educational chatbots (i.e., active mode) could lead to the knowledge-changing process in their actual user experiences (i.e., constructive activities). Researchers have also found that students' attitudes contribute to their engagement and interaction in online learning environments (Martin & Bolliger, 2018; Miao & Ma, 2022). The measures for emotional engagement and interaction include fun to use, enjoyable use, favorable feeling of use, and the stimulation of interests (Kuo et al., 2014; Martin & Rimm-Kaufman, 2015). Thus, students' attitudes toward the chatbot directly influence their user experiences, interaction, and engagement with the chatbot (Hobert, 2023). Consistent with this perspective, we propose the following three hypotheses:

- H2a: Students' attitudes toward using the chatbot have a positive relationship with their actual user experiences.
- H2b: Students' attitudes toward using the chatbot have a positive relationship with their learner-content interactions.
- H2c: Students' attitudes toward using the chatbot have a positive relationship with their emotional engagement.

Authors	Methods	Research focus
Savin-Baden et al. (2015)	Literature review	Students' emotional engagement and interactions with chatbots are vital to enhance online learning.
Pereira (2016)	Case study	Designing and evaluating a Telegram bot regarding students' engagement with course quizzes.
Fryer et al. (2017)	Experiment	Examining the effect of chatbot's novelty.
Crockett et al. (2017)	Experiments, fuzzy decision trees	Building a series of fuzzy predictive models to predict accurate learning styles.
Hien et al. (2018)	Experiment	FIT-EBot provides administrative and learning support to students.
Mckie & Narayan (2019)	Case study	The library chatbot has the potential to improve students' academic research experience.
Hobert (2019, 2023)	ICAP theory	Testing the ICAP theory for chatbot learning systems in programming education.
Lin & Chang (2020)	Mixed classroom study	The writing chatbot contributes to students' writing achievement.
Chatterjee & Bhattacharjee (2020)	Theory of acceptance and use of technology	Increasing acceptance and adoption of chatbots in India.
Rapp et al. (2021)	Literature review	Highlighting the importance of emotions and humanness in interaction with chatbots.
Shumanov & Johnson (2021)	Content analysis	Suggesting that matched consumer-chatbot personality improves sales and engagement.
Essel et al. (2022)	Quasi-experimental, focus groups	Students interacting with chatbots performed better academically compared with those with the instructor.
Liu et al. (2022)	Concept mapping	Chatbots increase interactive learning experience in a nonlinear environment.
Ait Baha et al. (2024)	Experiment	Chatbots create a supportive environment, encourage good interactions with students, allow learners to be more engaged, and achieve better academic objectives.
Aloqayli & Abdelhafez (2023)	Case study	Chatbots can be efficiently used for college admission.
Ayanwale & Ndlovu (2024)	Expanded diffusion theory of innovation	No direct relationships between perceived usefulness, perceived ease of use, and behavioral intention to use chatbots.
Wu & Yu (2024)	Meta-analysis	Chatbots have a large effect on students' learning outcomes with a short intervention duration.
Bilquise et al. (2024)	Technology acceptance model and self-determination theory	Examining factors that impact the willingness of students to accept chatbots.

Note. ICAP = interactive-constructive-active-passive.

Table 1. Studies of Educational Chatbots in Higher Education

The literature suggests that students' self-assessment of their learning experiences, known as perceived learning outcomes, can reflect their cognitive, behavioral, and affective learning processes (Alavi et al., 2002; Chen et al., 2015). In this paper we adopted Paechter et al.'s (2010) measurement scale, including students' self-reported grades, engagement, support, and satisfaction. Observing students' actual user experiences, social interactions, and emotional engagement is relatively easy in a face-to-face learning environment with experienced instructors (e.g., Holladay, 2017). However, in an online or blended learning environment, interacting with and engaging students are challenging (Wragg, 2019). Technological innovations such as the custom AI chatbot developed in this research can help improve student engagement and facilitate the transition of learning from passive to interactive for online learners (Essel et al., 2022; Lin & Chang, 2020). In the interactive mode, students' learner-content interactions and emotional engagement with the chatbot could enhance their perceived learning outcomes. Therefore, we propose the following three hypotheses:

- H3: Students' actual user experiences with the chatbot have a positive relationship with their perceived learning outcomes.
- H4: Students' learner-content interactions with the chatbot have a positive relationship with their perceived learning outcomes.
- H5: Students' emotional engagement with the chatbot has a positive relationship with their perceived learning outcomes.

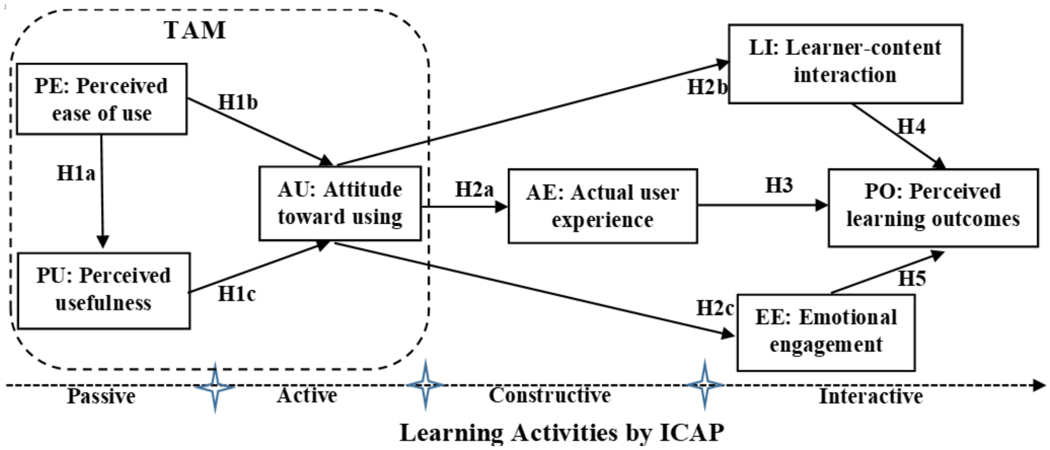


Figure 1. Conceptual Framework of Chatbot Enhanced Learning

2.4 Research Model

As generative AI technologies have been increasingly adopted in the educational context, we see a solid ground to integrate ICAP and TAM to study students' learning experiences involving generative AI. In particular, we propose key variables in the TAM model, such as perceived ease of use and perceived usefulness, that could shift learning from the passive mode to the active mode and consequently help catalyze a number of positive learning outcomes.

TAM is a well-established model commonly used to examine users' behavior intention in the context of technology-based tools adoption. Prior research has proven the predictive validity of TAM and its many variations for the assessment of diverse technological deployments in an educational context (Granić & Marangunić, 2019). The ICAP hypothesis predicts that as students become more engaged with learning materials, from passive to active to constructive to interactive, their learning experiences increase (Chi & Wylie, 2014). According to Holbert (2019), students' perceived ease of use of the chatbot and perceived usefulness fall into the passive mode, and their attitudes toward using turn in favor of the active mode. As a good proxy, their user experiences serve as constructive activities (Holbert, 2023). In this study, students' learner-content interactions and emotional engagement can be operationalized as the interactive mode. To better present the research framework, Figure 1 visualizes the conceptual model of the chatbot-enhanced perceived learning outcomes with seven factors and nine proposed hypotheses.

3. RESEARCH DESIGN

3.1 Custom AI Chatbot

To test the proposed research model, we developed a custom chatbot (Figure 2) for online and blended classes using OpenAI's application programming interface (API) and LlamaIndex, an open-source data framework. An API contains a set of rules or protocols that enable two software applications to communicate with each other to exchange data, features, and functionality. OpenAI's API (https://platform.openai.com) provides an interface that allows developers to integrate OpenAI's technologies with their own AI applications. Using this API, developers can create applications that send requests to OpenAI's models and receive information in return. The AI models that are currently supported by the OpenAI API include GPT-4, GPT-4 Turbo, GPT-3.5 Turbo, DALL-E, TTS, and Whisper (OpenAI Platform, n.d.-a).

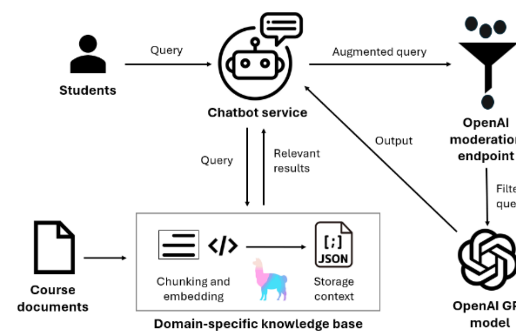


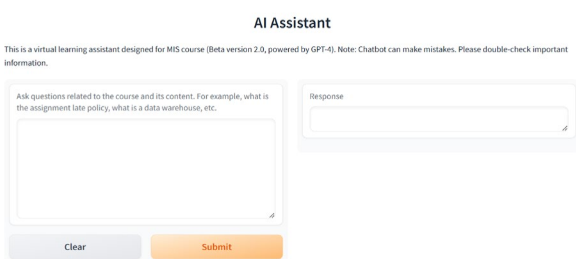
Figure 2. System Architecture of a Custom Artificial Intelligence Chatbot

Because OpenAI's GPT models are pretrained on a large amount of publicly available content from the Internet, they support only general requests to which the answers are commonly found in public online sources, including websites, blogs, forums, and news articles. For information in a specific context or domain, such as an ongoing course offered at a university or internal policies of a company, a knowledge base that contains domain-specific data needs to be created. In this study, we use LlamaIndex (https://www.llamaindex.ai/), a data framework with extensive retrieval-augmented generation (RAG) capabilities, to create custom knowledge bases and connect them to LLMs such as OpenAI's GPT models. RAG is a process that allows pretrained LLMs to retrieve information from an external knowledge base and combine it with their internal representation of information for language generation (Lewis et al., 2020). LlamaIndex supports a variety of data formats including text, pdf, Microsoft Word, Microsoft PowerPoint, JPEG images, MP3 audio, and MP4 video files

(LlamaIndex, n.d.). Any data in the allowed formats and relevant to the specific domain or context can be used for building the knowledge base. For this study, we created several knowledge bases using course-specific content, including course syllabi, schedules, assignment instructions, project descriptions, and examples.

LlamaIndex employs two key strategies to process documents and create knowledge bases for LLMs. First, it chunks documents into smaller contexts in the form of sentences or paragraphs; these chunks of data are referred to as nodes. These nodes can be efficiently processed by language models. Second, LlamaIndex indexes these nodes using vector embeddings, enabling fast and semantic search. An embedding is a vector representation of a piece of data (e.g., a text fragment) that is meant to preserve aspects of its content and/or its meaning (Almeida & Xexéo, 2019). Chunks of data that are similar in some way will tend to have embeddings that are closer together than unrelated data. After chunking and embedding, the content is then stored in the JSON format, creating a domain-specific knowledge base for the GPT model and can be queried by the chatbot.

As shown in Figure 3, students can access the chatbot through a web interface. Once a request is sent to the chatbot, it will first be examined by OpenAI's moderation endpoint. The moderation endpoint (OpenAI Platform, n.d.-b) is a tool in OpenAI's API that developers can use to check whether an input text contains harmful content and take actions as needed. The model classifies several harmful categories including hate, harassment, self-harm, sexuality, and violence (OpenAI Platform, n.d.-b). If a request is flagged as potentially harmful, then the request will be rejected, and the user will receive an error message. On the other hand, an unflagged request will be forwarded to the OpenAI GPT model, and the user will receive a response. Depending on the nature of the request, the response may be generated based on the domain-specific knowledge base or the general Internet content that are used to train the GPT models. Figure 3 shows the web interface of the chatbot for one of the participating courses.



Note. MIS = management information systems.

Figure 3. Web Interface of Custom Artificial Intelligence Chatbot

3.2 Participants
The chatbot was made available to 308 students enrolled in five business undergraduate classes offered at a major midwestern university in the United States during the spring and summer semesters of 2024. Of the five classes, two management information systems and two marketing classes were offered online asynchronously. One business class was offered in a blended format (75% online and 25% face-to-face). All are fundamental courses for undergraduate students in the business school. Table 2 summarizes information about the five classes participating in this study.

Course Title	Semester	Delivery Format
MIS xxx: Management Information Systems	Spring 2024	Asynchronous online
MIS xxx: Management Information Systems	Summer 2024	Asynchronous online
BUSN xxx: Business Analytics	Spring 2024	Blended
MRKT xxx: Foundations of Marketing	Spring 2024	Asynchronous online
MRKT xxx: Consumer Behavior	Spring 2024	Asynchronous online

Note. BUSN = business; MIS = management information systems; MRKT = marketing.

Table 2. List of Participating Classes

After using the chatbot for approximately two weeks, students were asked to complete a survey. A total of 255 responses were collected (a response rate of 82.79%). Out of the 255 respondents, 247 completed the entire survey, and among them, 206 students reported that they used the chatbot at least once. Consequently, these 206 valid samples were used in the analysis (a valid response rate of 80.78%). As a general guideline, a sample size exceeding 200, with 10 to 15 indicators per variable, is considered sufficient for structural equation monitoring (Kline, 2023). Table 3 shows the demographic and the chatbot using information from the survey respondents.

4. DATA ANALYSIS AND RESULTS

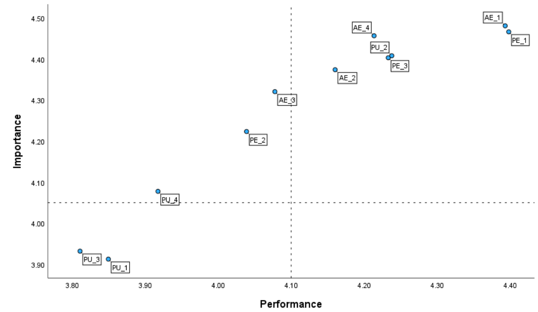
4.1 Common Method Bias
The common method bias (CMB) test has been widely used to determine whether samples are influenced by bias. This study adopts Harman's single-factor test using IBM SPSS Statistics 29 to examine CMB in the data. We included all the items measuring the constructs and set 1 as the fixed number of factors. If one factor accounts for more than 50% of the total variance extracted, it suggests the presence of CMB in the study. In our data, the total variance extracted by one factor is 45.49% (<50%), indicating that there is no statistically significant CMB in the study.

4.2 Importance-Performance Analysis
As a graphical tool developed by Martilla and James (1977), importance-performance analysis has been a popular approach for decades to examine the strengths and weaknesses of products and services (Baek, 2021). It has been widely used in educational evaluations to identify the underperformed and over-performed teaching elements (Chen et al., 2022; Sumampouw et al., 2024). In this research, we measured perceived ease of use, perceived usefulness, attitude toward using, and actual user experience by adapting the scales of Masrom (2007) because it is one of the first studies that

examined the TAM's influencing factors in e-learning contexts. The detailed value of both importance and performance for the factors with 11 corresponding items can be found in Appendix A. There are three major aspects with high importance, but relatively low performance that we should concentrate on: (1) improving the chatbot's perceived ease of use, specifically its integration with the course (PE_2); (2) improving the chatbot's perceived usefulness, especially the learning effectiveness (PU_4); and (3) improving the chatbot's actual user experience, particularly by providing answers precisely (AE_3). Notably, more than half of the items (6 out of 11) have received high values in both importance and performance, indicating that our chatbot has performed well and fits the students' needs (Figure 4). Only two items (improve course performance and increase course productivity) related to perceived usefulness (PU_1 and PU_3) have low importance and performance, indicating that these items are not critical issues with high priority, but they could be the focus of future work.

Variable	No.	%
Age		
18-19	31	15.05
20-22	157	76.21
23-29	14	6.80
≥30	4	1.94
Gender		
Male	113	54.85
Female	92	44.66
Prefer not to respond	1	0.49
Prior Experience		
Used in other courses	34	16.51
Not used	159	77.18
Maybe (unsure or can't remember)	13	6.31
Using frequency		
1-2 times	158	76.70
3-4 times	26	12.62
5 or more times	22	10.68
Using minutes		
1-4 minutes	26	12.62
5-10 minutes	117	59.80
11-20 minutes	40	19.42
21-30 minutes	13	6.31
≥31 minutes	10	4.85
Using purpose		
To find general information about the course.	21	10.19
Information about projects, assignments, and/or tests.	38	18.45
To better learn the content covered in the course.	20	9.71
All of the above	88	42.72
No specific purpose, my professor asked me to use it.	39	18.93

Table 3. Survey Respondents' Demographic and Chatbot Usage Information



Note. AE = actual user experience; PE = perceived ease of use; PU = perceived usefulness.

Figure 4. Evaluation Quadrant of Importance-Performance Analysis

4.3 Confirmatory Factor Analysis

To test the construct reliability, we carried out confirmatory factor analysis on the 206 samples. According to Hair et al. (2006), confirmatory factor analysis must have acceptable model fit indices including chi-square/degrees of freedom ($\chi2/df$) < 3.00, comparative fit index (CFI) > 0.90, normed fit index (NFI) > 0.90, relative fit index (RFI) > 0.90, incremental fit index (IFI) > 0.90, and root mean square error of approximation (RMSEA) < 0.06.

Given the modest sample size, we decided to remove some items with relatively low factor loading (< 0.60) to avoid overfitting the measurement model. Based on the analysis results, two items were dropped to further improve the model fit. The item "it provides very useful course information" (factor loading = 0.50) was removed from perceived usefulness, and "the chatbot answers queries quickly" (factor loading = 0.51) was removed from actual user experience. In perceived usefulness, the other three remaining items (i.e., "The chatbot improves my course performance," "It helps increase my course productivity," and "It helps enhance my enhance learning experience") are more specific types of usefulness. Regarding actual user experience, quickness is unlikely to be a user concern because the course chatbot usually replies to students within a few seconds. Therefore, the other three items ("The chatbot answers queries completely," "It answers queries precisely," and "It provides answers that are easy to extract") with higher factor loading remain. Afterward, seven factors with 22 items remain in the model. The measurement model shows very good model fit criteria, with acceptable model fit indices ($\chi2/df$ = 1.70, CFI = 0.97, NFI = 0.92, Tucker-Lewis Index = 0.96, IFI = 0.97, and RMSEA = 0.05) and satisfactory values of the average variance extracted (AVE; > 0.50) and composite reliability (CR; > 0.70) in all factors. All the 22 items are retained for structural equation modeling. Table 4 shows the related estimates.

Regarding the extent of dissimilarity between different factors, AVE was used to measure discriminant validity. The square root of the AVE also needs to exceed the inter-construct correlations (Hair et al., 2006). The square root of each construct's AVE has a greater value than the inter-construct correlations, indicating good discriminant validity. More details are included in Appendix B.

Factors and items	St. F.L.	AVE	C.R.	P
Perceived ease of use (PE)		0.57	0.80	
The chatbot is easy to use (PE_1)	0.71			***
It is well-integrated with the course (PE_2)	0.77			***
It is interacted with understandably (PE_3)	0.79			***
Perceived usefulness (PU)		0.75	0.90	
The chatbot improves my course performance (PU_1)	0.83			***
It helps increase my course productivity (PU_3)	0.88			***
It helps enhance my learning effectiveness (PU_4)	0.89			***
Actual user experience (AE)		0.68	0.86	
The chatbot answers queries completely (AE_2)	0.85			***
It answers queries precisely (AE_3)	0.87			***
It provides answers that are easy to extract (AE_4)	0.75			***
Attitude toward using (AU)		0.80	0.92	
I like the idea of using the chatbot in the course (AU_1)	0.88			***
I have a generally favorable attitude toward using chatbot (AU_2)	0.89			***
It is a good idea to use the chatbot to engage with course activities (AU_3)	0.90			***
Learner-content interaction (LI)		0.66	0.85	
The chatbot stimulates my interest in this course (LI_1)	0.72			***
It helps me understand better the class content (LI2_)	0.85			***
It helps with new concepts or new knowledge in the course (LI_3)	0.85			***
Emotional engagement (EE)		0.80	0.92	
The chatbot is fun to use (EE_1)	0.83			***
I enjoy using the chatbot in the course (EE_2)	0.93			***
I like the feeling of using the chatbot in the course (EE_3)	0.92			***
Perceived learning outcomes (PO)		0.72	0.91	
I am more confident in getting a higher grade (PO_1)	0.75			
I am more engaged with the course after using the chatbot (PO_2)	0.88			***
I feel more support in the course after using the chatbot (PO_3)	0.83			***
I am more satisfied with the course after using the chatbot (PO_4)	0.92			***

Note. St. F. L.= Standardized factor loading; AVE= average variance extracted; C.R.=composite reliability.
*** $p < 0.001$.

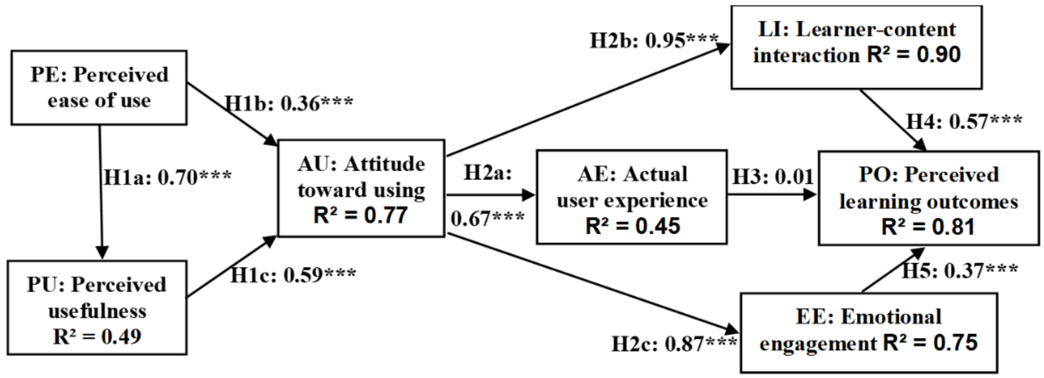
Table 4. The Estimates of CFA

4.4 Path Modeling

Using Amos 29.0, we performed partial least squares path modeling (also known as partial least squares structural equation modeling) to further investigate the relationships between the factors. Path modeling is usually preferable for a modest sample size because it can predict relationships with limited data better than other methods (Hair et al., 2012). The indices of the partial least squares structural equation modeling model are acceptable, with $\chi^2/df = 1.83$, RMSEA = 0.05, NFI = 0.91, TLI = 0.95, IFI = 0.96, and CFI = 0.96. The results reveal that perceived ease of use has a positive and statistically significant influence on perceived usefulness and attitude toward using, so hypotheses H1a and H1b are supported. Perceived usefulness has a positive and statistically significant influence on attitude toward using, thus supporting hypothesis H1c. Attitude toward using has positive and statistically significant influences on the actual user experience, learner-content interaction, and emotional engagement, lending full support to hypotheses H2a, H2b, and H2c. However, actual user experience does not have a statistically significant effect on perceived learning outcomes; therefore, hypothesis H3 is rejected. This weak relationship may be caused by the relatively low performance of actual user experience, and in particular, the IPA revealed that answering queries precisely (AE_3) can be improved. Lastly, both learner-content interaction and emotional engagement have positive and statistically significant effects on perceived learning outcomes. Therefore, hypotheses H4 and H5 are supported. Figure 5 presents the research model with path coefficients and their corresponding significant level at 0.1%.

4.5 Content Analysis

In addition to hypothesis testing, we conducted an ad hoc analysis of responses to the open-ended question about overall chatbot perception and desired future capabilities. Using a script created with R version 4.3.0, we performed content analysis on the textual data and applied lexicon-based sentiment analysis to identify sentiment-carrying words and derive the emotion and sentiment scores. The National Research Council Canada word-emotion association lexicon (Mohammad & Turney, 2010) was used to extract emotion words. Figure 6 presents a word cloud of the most frequent words, where size indicates frequency or importance.



Note. R2 = coefficient of determination.
*** p < 0.001.

Figure 5. Standardized Results of Path Modeling

Although the word cloud offers some insights into the most frequent concepts derived from user responses, these findings are preliminary. Therefore, cross-checking the results by reviewing the responses to validate the insights reported was essential. After we reviewed both the results from the word cloud and the user comments, the key terms identified in the word cloud apparently suggested that, in the next version of the chatbot, students expect the chatbot to provide more specific answers to their questions, especially those related to course information, course schedule, and assignments. These findings provide supporting evidence for specific chatbot features that can enhance its usefulness, which could subsequently foster students' positive attitudes toward using the chatbot, as suggested in the proposed research model.

Figure 6. Graphic Results of the Word Cloud

We also conducted sentiment analysis to analyze the emotions and sentiments expressed in the responses to the survey's open-ended questions. Figure 7 displays the average scores of emotions and sentiments contained in the comments. The results suggest that most of the respondents had a positive overall experience with the chatbot. Trust received the highest average score (0.174), whereas disgust and anger both received the lowest scores (0.005). We also examined sentiment polarity with regard to whether a comment was positive, negative, or neutral. For each comment, we determined a sentiment polarity score, and, ranging from 0 to 1, the results show that the mean value of positive emotion is 0.301, and the mean value of negative emotion is 0.019. These data clearly indicate that the students generally had positive attitudes toward the chatbot and perceived it as trustworthy. These results can be used as guidelines to further customize the features of the chatbot to improve the effectiveness of the educational chatbot in the future.

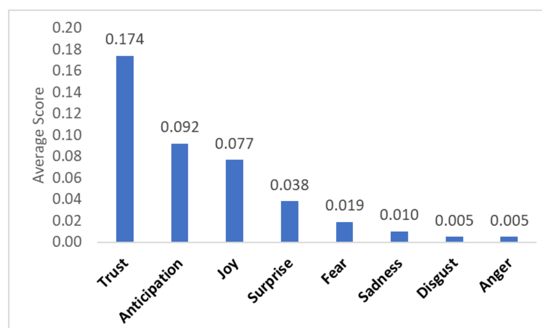


Figure 7. Average Emotion Scores

5. DISCUSSION

5.1 Summary of the Findings

Based on the TAM and ICAP theories, this research extends the previous studies by developing and examining the influences of an educational chatbot on students' perceptions and responses. The results reveal that perceived ease of use increases perceived usefulness, and both contribute to attitude toward using. Our findings also suggest that attitude toward using increases actual user experience, emotional engagement, and learner-content interaction. Notably, learning content interaction and emotional engagement have statistically significant and positive contributions (the standard coefficients are 0.57*** and 0.37***, respectively) to perceived learning outcomes. Except for the statistically insignificant relationship between actual user experience and perceived learning outcomes, all the other proposed hypotheses are supported at the 0.1% significant level.

Sentiment analysis was further conducted on the students' comments in the survey. The results reveal that students generally used the chatbot to find information about the course, schedule, and assignments. Emotions and sentiments extracted from the comments indicate that students expressed interest and positive emotions toward the chatbot. Students reported that they enjoyed using the chatbot and considered the chatbot trustworthy. These findings shed light on the effectiveness and opportunities of incorporating AI technologies into higher education.

5.2 Theoretical Contributions

This research contributes to the advancement of pedagogical and psychological learning theories related to AI chatbots in higher education. This study proposes a research model that integrates and extends the TAM and ICAP theories to e-learning environments in online business education. Our findings confirm results of prior research that perceived ease of use and perceived usefulness are two key antecedents that affect the acceptance of technology in e-learning. These results add to the development of the TAM theory in technology-enhanced modern education.

Guided by the ICAP framework, we provide evidence of the positive effects of user acceptance and user experience on interaction and emotional engagement with new technology. Our findings reveal that, as students seek help from the chatbot for course information and learning materials, their learning engagement moves from the passive mode (e.g., reading textbooks or watching lecture videos without doing anything else) to the interactive mode (e.g., interacting with the chatbot on course-related questions). Subsequently, students' attitudes toward using the chatbot change positively, the actual user experience is enhanced, and as a result, perceived learning outcomes are improved. More specifically, generative AI chatbots present opportunities for online students not only to passively receive instructional materials but also actively manipulate information and engage in constructive and interactive dialog with chatbots. To use chatbots designed for their classes, students need to formulate questions in their own words (constructive mode) if not copied from instructor-provided content (active mode). Therefore, students' actual user experiences correspond to enhanced learning, but have statistically insignificant effects on perceived learning outcomes. This finding suggests that, in the context of chatbot-assisted e-learning, the actual user experience may not have impacts on perceived learning outcomes as direct and significant as expected. In comparison, emotional engagement and learner-content interaction are important factors to improve students' perceived learning outcomes. It also implies that additional factors may be added to the research framework to further explore the complex theoretical dynamics in an e-learning environment.

5.3 Practical Implications

From a practical perspective, this research provides some implications for online education. Our findings shed light on how generative AI technology helps improve the e-learning experience, highlighting the effectiveness of such technology in support of social interaction and emotional engagement in higher education. Because the students participating in this study were either enrolled in online classes or blended classes with a significant online learning component, the instructor-student and student-student interactions were very limited. For example, we observed that, in one of the online MIS classes, less than 25% of the students had at least one contact with the instructor either by email or meeting during the instructor's office hours. For this class, four discussion forums were created during the semester, and the students were encouraged to contribute to the discussions and earn bonus points. However, 62 of 103 students (60%) never participated in any of the discussion forums. The data show that most students in the class were reluctant to interact with the instructor or other students in the same class. On the other hand, 72 of 103 students (70%) used the chatbot at least once and participated in the chatbot survey. We believe that a well-trained AI chatbot can fill the interaction gap and work as a virtual assistant/learning companion to online students, interacting with them whenever needed, contributing to their problem solving, and improving their emotional engagement in learning.

To the best of our knowledge, this is one of the first studies that developed and tested an AI chatbot for e-learning based on the RAG framework. This study demonstrates the feasibility and practicality of implementing and deploying such technologies. We developed the chatbot described in this paper using LlamaIndex, an open-source RAG framework. The total development time including testing was approximately 2 months, and the programs were written in Python and hosted on Hugging Face, a public machine learning and data science community platform (https://huggingface.co/). The pretrained LLM model underlying the current version of the chatbot is OpenAI's GPT-4. There is a small fee associated with using the model through the OpenAI API, but the cost is minimum for class use (OpenAI, n.d.). Because LlamaIndex integrates with many popular LLMs, instructors or developers who wish to test different LLM models for their AI agents can easily switch to other models, such as Gemini and Claude. Instructors can also opt for no-code options to develop their custom chatbots. For example, users can create their own chatbots using OpenAI GPT builder (https://chatgpt.com/gpts), a graphical development environment where custom chatbots can be built with a few simple steps. Microsoft Copilot Studio (https://www.microsoft.com/en-us/microsoft-copilot/microsoft-copilot-studio) has similar capabilities.

This research contributes to a better understanding of the roles of AI chatbots in affecting students' perceptions and responses; this improved understanding can help instructors develop pedagogical approaches that enhance the e-learning experience and perceived learning outcomes. Our findings also suggest the importance of two aspects, ease of use and usefulness, in affecting attitudes toward chatbots. The empirical findings indicate that AI chatbots are favorably perceived by students, which might be conditioned by the chatbots' ease of use and usefulness. Poorly designed chatbots may generate a less favorable outcome. Results from our importance-performance analysis indicate that users regard the following features of a chatbot as highly important: being easy to use, interacting in an understandable way, providing useful course information, responding quickly, and providing answers that are easy to extract. When designing a custom chatbot for specific classes and learners, instructors should pay attention to not only domain-specific content but also the user interface and performance of the chatbot. Human-computer interaction concepts such as usability design can be used to improve or customize the chatbot to increase its ease of use and usefulness. Furthermore, according to the results of the sentiment analysis, chatbot designers can implement user experience design concepts (e.g., Hassenzahl, 2013) to improve the chatbot's anthropomorphic characteristics, which can subsequently promote trust and positive emotions.

5.4 Limitations and Future Work

This study has several limitations that underline the need for future research. As suggested by previous research, technology platforms may have different impacts on student learning and faculty teaching. Although the chatbot designed for this research was well received by the participants, it is important to note that we focused on only online and blended classes in this study. It is unclear whether students in traditional face-to-face classes will derive similar benefits from using AI chatbots. Furthermore, college classes vary in teaching styles, formats, and subject areas. Students enrolled in different types of classes (e.g., lecture, seminar, and hands-on) in various disciplines may benefit from such platforms differently. Future studies should examine the factors that influence student involvement and use of AI agents to increase the effectiveness of such technology in e-learning and traditional classroom learning. In future research, multidisciplinary studies should be conducted to investigate how students use custom chatbots in classes taught in different formats and disciplines.

We speculate that our findings might be influenced by data and technical limitations—a common issue in empirical studies. Students' written comments further suggest aspects for future improvement, including the chatbot's integration with courses, learning effectiveness, and precise answers. The current version of the chatbot is adept at answering user queries and summarizing documents, but it falls short of initiating conversations or leading discussions. Future development of the chatbot should focus on improving its knowledge base and conversation skills, as well as developing capabilities for adaptive learning.

In addition, in this study we conducted content analysis on only the written feedback provided by the participants in the survey and did not collect the complete use data of the chatbot. For future work, we will continue to improve the conversional capabilities of the chatbot and collect and analyze interactions between users and the chatbot. Such data can be used for in-depth content and sentiment analysis to examine the relationships between specific chatbot features and user experience and emotions. Longitudinal studies on how students perceive the chatbot at different stages of the learning experience could also be beneficial, shedding light on potential changes in students' perception and attitude toward AI chatbots and the possible changing effects on their perceived learning outcomes. Finally, this research investigates the benefits and opportunities of AI chatbots only from the learners' perspective. It would be interesting to collect feedback and input from course instructors who may have different viewpoints through their experiences with the AI chatbots.

6. CONCLUSIONS

The transformation from the traditional classroom to the e-learning environment is not only challenging for educators but also for students. Integrating a custom educational chatbot into online and blended classes, we combined in this study the TAM and ICAP theories to investigate the complex dynamics in e-learning and how AI chatbots can help facilitate constructive and interactive learning. The study sheds light on the effectiveness and opportunities of incorporating generative AI into higher education.

7. REFERENCES

Adamopoulou, E., & Moussiades, L. (2020). An Overview of Chatbot Technology. In I. Maglogiannis, L. Iliadis, & E. Pimenidis (Eds.), *Artificial Intelligence Applications and Innovations*. *AIAI 2020. IFIP Advances in Information and Communication Technology, Vol 584*. Springer, Cham. https://doi.org/10.1007/978-3-030-49186-4_31

Ait Baha, T., El Hajji, M., Es-Saady, Y., & Fadili, H. (2024). The Impact of Educational Chatbot on Student Learning Experience. *Education and Information Technologies*, 29, 10153-10176. https://doi.org/10.1007/s10639-023-12166-w

Almeida, F., & Xexéo, G. (2019). Word Embeddings: A Survey. arXiv preprint arXiv:1901.09069.

Aloqayli, A., & Abdelhafez, H. (2023). Intelligent Chatbot for Admission in Higher Education. *International Journal of Information and Education Technology*, 13(9), 1348-1357. https://doi.org/10.18178/ijiet.2023.13.9.1937

Alavi, M., Marakas, G. M., & Yoo, Y. (2002). A Comparative Study of Distributed Learning Environments on Learning Outcomes. *Information Systems Research*, 13(4), 404-415. https://doi.org/10.1287/isre.13.4.404.72

Al-Abdullatif, A. M. (2023). Modeling Students' Perceptions of Chatbots in Learning: Integrating Technology Acceptance With the Value-Based Adoption Model. *Education Sciences*, 13(11), 1151. https://doi.org/10.3390/educsci13111151

Ayanwale, M. A., & Ndlovu, M. (2024). Investigating Factors of Students' Behavioral Intentions to Adopt Chatbot Technologies in Higher Education: Perspective From Expanded Diffusion Theory of Innovation. *Computers in Human Behavior Reports*, 100396. https://doi.org/10.1016/j.chbr.2024.100396

Baek, C. (2021). A Study on Consumer Strategy of Artificial Intelligence Service Using Importance-Satisfaction Analysis. *Global Business & Finance Review*, 26(2), 110-120. https://doi.org/10.17549/gbfr.2021.26.2.110

Bilquise, G., Ibrahim, S., & Salhieh, S. M. (2024). Investigating Student Acceptance of an Academic Advising Chatbot in Higher Education Institutions. *Education and Information Technologies*, 29(5), 6357-6382. https://doi.org/10.1007/s10639-023-12076-x

Castro, M. D. B., & Tumibay, G. M. (2021). A Literature Review: Efficacy of Online Learning Courses for Higher Education Institution Using Meta-Analysis. *Education and Information Technologies*, 26, 1367-1385. https://doi.org/10.1007/s10639-019-10027-z

Chatterjee, S., & Bhattacharjee, K. K. (2020). Adoption of Artificial Intelligence in Higher Education: A Quantitative Analysis Using Structural Equation Modelling. *Education and Information Technologies*, 25, 3443-3463. https://doi.org/10.1007/s10639-020-10159-7

Chen, H.-L., Vicki Widarso, G., & Sutrisno, H. (2020). A Chatbot for Learning Chinese: Learning Achievement and Technology Acceptance. *Journal of Educational*

Computing Research, 58(6), 1161-1189. https://doi.org/10.1177/0735633120929622

Chen, J.-A., Tu, Y.-F., Hwang, G.-J., & Wu, J.-F. (2022). University Librarians' Perspectives on an Importance-Performance Analysis of Authentication System Attributes and Their Attitudes Towards Authentication Log Visualization. *The Journal of Academic Librarianship*, 48(4), 102528. https://doi.org/10.1016/j.acalib.2022.102528

Chen, L., Keys, A., & Gaber, D. (2015). How Does ERPsim Influence Students' Perceived Learning Outcomes in an Information Systems Course? An Empirical Study. *Journal of Information Systems Education*, 26(2), 135-146.

Chi, M. T. H. (2009). Active-Constructive-Interactive: A Conceptual Framework for Differentiating Learning Activities. *Topics in Cognitive Science*, 1(1), 73-105. https://doi.org/10.1111/j.1756-8765.2008.01005.x

Chi, M. T. H., & Wylie, R. (2014). The ICAP Framework: Linking Cognitive Engagement to Active Learning Outcomes. *Educational Psychologist*, 49(4), 219-243. https://doi.org/10.1080/00461520.2014.965823

Colace, F., De Santo, M., Lombardi, M., Pascale, F., Pietrosanto, A., & Lemma, S. (2018). Chatbot for e-Learning: A Case of Study. *International Journal of Mechanical Engineering and Robotics Research*, 7(5), 528-533. https://doi.org/10.18178/ijmerr.7.5.528-533

Crockett, K., Latham, A., & Whitton, N. (2017). On Predicting Learning Styles in Conversational Intelligent Tutoring Systems Using Fuzzy Decision Trees. *International Journal of Human-Computer Studies*, 97, 98-115. https://doi.org/10.1016/j.ijhcs.2016.08.005

Curtain, R. (2002). *Online Delivery in the Vocational Education and Training Sector: Improving Cost Effectiveness*. Australian National Training Authority. https://www.ncver.edu.au/__data/assets/file/0027/9648/online-delivery-in-vet-sector-782.pdf

Davis, F. D. (1989). Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. *MIS Quarterly*, 13(3), 319-340. https://doi.org/10.2307/249008

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User Acceptance of Computer Technology: A Comparison of Two Theoretical Models. *Management Science*, 35(8), 982-1003. https://doi.org/10.1287/mnsc.35.8.982

Essel, H. B., Vlachopoulos, D., Tachie-Menson, A., Johnson, E. E., & Baah, P. K. (2022). The Impact of a Virtual Teaching Assistant (Chatbot) on Students' Learning in Ghanaian Higher Education. *International Journal of Educational Technology in Higher Education*, 19(1), 57. https://doi.org/10.1186/s41239-022-00362-6

Farhan, M., Munwar, I. M., Aslam, M., Martinez Enriquez, A. M., Farooq, A., Tanveer, S., & Mejia, A. P. (2012). Automated Reply to Students' Queries in e-Learning Environment Using Web-BOT. In *Proceedings of the 11th Mexican International Conference on Artificial Intelligence* (pp. 63-65). IEEE. https://doi.org/10.1109/MICAI.2012.18

Fryer, L. K., Ainley, M., Thompson, A., Gibson, A., & Sherlock, Z. (2017). Stimulating and Sustaining Interest in a Language Course: An Experimental Comparison of Chatbot and Human Task Partners. *Computers in Human Behavior*, 75, 461-468. https://doi.org/10.1016/j.chb.2017.05.045

Gong, M., Xu, Y., & Yu, Y. (2004). An Enhanced Technology Acceptance Model for Web-Based Learning. *Journal of Information Systems Education*, 15(4), 365-374.

Granić, A., & Marangunić, N. (2019). Technology Acceptance Model in Educational Context: A Systematic Literature Review. *British Journal of Educational Technology*, 50(5), 2572-2593. https://doi.org/10.1111/bjet.12864

Gupta, S., & Chen, Y. (2022). Supporting Inclusive Learning Using Chatbots? A Chatbot-Led Interview Study. *Journal of Information Systems Education*, 33(1), 98-108.

Hair, J. F., Black, B., Babin, B., & Anderson, R. (2006) *Multivariate Data Analysis* (6th Ed.). Pearson Prentice Hall.

Hair, J. F., Sarstedt, M., Ringle, C. M., & Mena, J. A. (2012). An Assessment of the Use of Partial Least Squares Structural Equation Modeling in Marketing Research. *Journal of the Academy of Marketing Science*, 40, 414-433. https://doi.org/10.1007/s11747-011-0261-6

Hassenzahl, M. (2013). User Experience and Experience Design. *The Encyclopedia of Human-Computer Interaction*, 2, 1-14.

Hien, H. T., Cuong, P.-N., Nam, L. N. H., Nhung, H. L. T. K., & Thang, L. D. (2018). Intelligent Assistants in Higher-Education Environments: The FIT-Ebot, A Chatbot for Administrative and Learning Support. In *SoICT '18: Proceedings of the 9th International Symposium on Information and Communication Technology* (pp. 69-76). Association for Computing Machinery. https://doi.org/10.1145/3287921.3287937

Hobert, S. (2019). Say Hello to 'Coding Tutor'! Design and Evaluation of a Chatbot-Based Learning System Supporting Students to Learn to Program. In *ICIS 2019: Proceedings of the 40th International Conference on Information Systems*. Association for Information Systems.

Hobert, S. (2023). Fostering Skills with Chatbot-Based Digital Tutors–Training Programming Skills in a Field Study. *i-com*, 22(2), 143-159. https://doi.org/10.1515/icom-2022-0044

Holladay, P. J. (2017). Chapter 10: Pedagogy for Online Tourism Classes. In P. Benckendorff & A. Zehrer (Eds.), *Handbook of Teaching and Learning in Tourism*. Edward Elgar Publishing. https://doi.org/10.4337/9781784714802.00018

Jackson, M. J., & Helms, M. M. (2008). Student Perceptions of Hybrid Courses: Measuring and Interpreting Quality. *Journal of Education for Business*, 84(1), 7-12. https://doi.org/10.3200/JOEB.84.1.7-12

Kline, R. B. (2023). *Principles and Practice of Structural Equation Modeling* (5th ed.). The Guilford Press.

Kuo, Y.-C., Walker, A. E., Schroder, K. E. E., & Belland, B. R. (2014). Interaction, Internet Self-Efficacy, and Self-Regulated Learning as Predictors of Student Satisfaction in Online Education Courses. *The Internet and Higher Education*, 20, 35-50. https://doi.org/10.1016/j.iheduc.2013.10.001

Lewis, P., Perez, E., Piktus, A., Petroni, F., Karpukhin, V., Goyal, N., Küttler, H., Lewis, M., Yih, W.-T., Rocktäschel, T., Riedel, S., & Kiela, D. (2020). Retrieval-Augmented Generation for Knowledge-Intensive NLP Tasks. In H. Larochelle, M. Ranzato, R. Hadsell, M. F. Balcan, & H. Lin (Eds.), *Advances in Neural Information Processing Systems (NeurIPS 2020)*, 33, 9459-9474.

Lin, M. P. C., & Chang, D. (2020). Enhancing Post-Secondary Writers' Writing Skills With a Chatbot: A Mixed-Method Classroom Study. *Educational Technology & Society*, 23(1), 78-92.

Liu, L., Subbareddy, R., & Raghavendra, C. G. (2022). AI Intelligence Chatbot to Improve Students Learning in the Higher Education Platform. *Journal of Interconnection Networks*, 22(Supp02), 2143032. https://doi.org/10.1142/S0219265921430325

LlamaIndex. (n.d.). Component Guides. https://docs.llamaindex.ai/en/stable/module_guides/

Martilla, J. A., & James, J. C. (1977). Importance-Performance Analysis. *Journal of Marketing*, 41(1), 77-79. https://doi.org/10.2307/1250495

Martin, D. P., & Rimm-Kaufman, S. E. (2015). Do Student Self-Efficacy and Teacher-Student Interaction Quality Contribute to Emotional and Social Engagement in Fifth Grade Math? *Journal of School Psychology*, 53(5), 359-373. https://doi.org/10.1016/j.jsp.2015.07.001

Martin, F., & Bolliger, D. U. (2018). Engagement Matters: Student Perceptions on the Importance of Engagement Strategies in the Online Learning Environment. *Online Learning*, 22(1), 205-222. https://doi.org/10.24059/olj.v22i1.1092

Masrom, M. (2007). Technology Acceptance Model and e-Learning [Paper presentation]. *The 12th International Conference on Education*, Brunei Darussalam.

Mckie, I. A. S., & Narayan, B. (2019). Enhancing the Academic Library Experience With Chatbots: An Exploration of Research and Implications for Practice. *Journal of the Australian Library and Information Association*, 68(3), 268-277. https://doi.org/10.1080/24750158.2019.1611694

Miao, J., & Ma, L. (2022). Students' Online Interaction, Self-Regulation, and Learning Engagement in Higher Education: The Importance of Social Presence to Online Learning. *Frontiers in Psychology*, 13, 815220. https://doi.org/10.3389/fpsyg.2022.815220

Miller, A., Topper, A. M., & Richardson, S. (2017). *Suggestions for Improving IPEDS Distance Education Data Collection*. U.S. Department of Education. Washington, DC: National Postsecondary Education Cooperative. https://nces.ed.gov/ipeds/pdf/NPEC/data/NPEC_Paper_IPEDS_Distance_Education_2017.pdf

Mohammad, S., & Turney, P. (2010). Emotions Evoked by Common Words and Phrases: Using Mechanical Turk to Create an Emotion Lexicon. In *Proceedings of the NAACL HLT 2010 Workshop on Computational Approaches to Analysis and Generation of Emotion in Text* (pp. 26-34).

National Center for Education Statistics. (n.d.). *Fast Facts: Distance Learning*. https://nces.ed.gov/fastfacts/display.asp?id=80

Nenkov, N., Dimitrov, G., Dyachenko, Y., & Koeva, K. (2016). Artificial Intelligence Technologies for Personnel Learning Management Systems. In *Proceedings of the 2016 IEEE 8th International Conference on Intelligent Systems* (pp. 189-195). IEEE. https://doi.org/10.1109/IS.2016.7737420

OpenAI. (2022). *Introducing ChatGPT*. https://openai.com/index/chatgpt/

OpenAI. (n.d.). *API Pricing*. https://openai.com/api/pricing/

OpenAI Platform. (n.d.-a). *Models*. https://platform.openai.com/docs/models

OpenAI Platform. (n.d.-b). *Moderation*. https://platform.openai.com/docs/guides/moderation

Paechter, M., Maier, B., & Macher, D. (2010). Students' Expectations of, and Experiences in e-Learning: Their Relation to Learning Achievements and Course Satisfaction. *Computers & Education*, 54(1), 222-229. https://doi.org/10.1016/j.compedu.2009.08.005

Pereira, J. (2016). Leveraging Chatbots to Improve Self-Guided Learning Through Conversational Quizzes. In *TEEM '16: Proceedings of the Fourth International Conference on Technological Ecosystems for Enhancing Multiculturality* (pp. 911-918). Association for Computing Machinery. https://doi.org/10.1145/3012430.3012625

Rapp, A., Curti, L., & Boldi, A. (2021). The Human Side of Human-Chatbot Interaction: A Systematic Literature Review of Ten Years of Research on Text-Based Chatbots. *International Journal of Human-Computer Studies*, 151, 102630. https://doi.org/10.1016/j.ijhcs.2021.102630

Saif, N., Khan, S. U., Shaheen, I., ALotaibi, F. A., Alnfiai, M. M., & Arif, M. (2024). Chat-GPT: Validating Technology Acceptance Model (TAM) in Education Sector via Ubiquitous Learning Mechanism. *Computers in Human Behavior*, 154, 108097. https://doi.org/10.1016/j.chb.2023.108097

Santhanam, R., Sasidharan, S., & Webster, J. (2008). Using Self-Regulatory Learning to Enhance e-Learning-Based Information Technology Training. *Information Systems Research*, 19(1), 26-47. https://doi.org/10.1287/isre.1070.0141

Savin-Baden, M., Tombs, G., & Bhakta, R. (2015). Beyond Robotic Wastelands of Time: Abandoned Pedagogical Agents and New Pedalled Pedagogies. *E-Learning and Digital Media*, 12(3-4), 295-314. https://doi.org/10.1177/2042753015571835

Shumanov, M., & Johnson, L. (2021). Making Conversations With Chatbots More Personalized. *Computers in Human Behavior*, 117, 106627. https://doi.org/10.1016/j.chb.2020.106627

Singh, V., & Thurman, A. (2019). How Many Ways Can We Define Online Learning? A Systematic Literature Review of Definitions of Online Learning (1988-2018). *American Journal of Distance Education*, 33(4), 289-306. https://doi.org/10.1080/08923647.2019.1663082

Sumampouw, M. G., Wikarsa, L., & Rumondor, A. M. (2024). Application of Importance Performance Analysis Method for Service Identification in the Learning Process. *Journal of Information Technology and Its Utilization*, 7(1), 9-18. https://doi.org/10.56873/jitu.7.1.5577

Sreelakshmi, A. S., Abhinaya, S. B., Nair, A., & Nirmala, S. J. (2019). A Question Answering and Quiz Generation Chatbot for Education. In *Proceedings of the 2019 Grace Hopper Celebration India (GHCI)* (pp. 1-6). IEEE. https://doi.org/10.1109/GHCI47972.2019.9071832

Tayebinik, M., & Puteh, M. (2013). Blended Learning or e-Learning? arXiv (preprint) arXiv:1306.4085 [cs.CY]. https://doi.org/10.48550/arXiv.1306.4085

Wollny, S., Schneider, J., Di Mitri, D., Weidlich, J., Rittberger, M., & Drachsler, H. (2021). Are We There Yet? — A Systematic Literature Review on Chatbots in Education. *Frontiers in Artificial Intelligence*, 4, 654924. https://doi.org/10.3389/frai.2021.654924

Wragg, N. (2019). Online Communication Design Education: The Importance of the Social Environment. *Studies in Higher Education*, 45(11), 2287-2297. https://doi.org/10.1080/03075079.2019.1605501

Wu, R., & Yu, Z. (2024). Do AI Chatbots Improve Students Learning Outcomes? Evidence From a Meta-Analysis. *British Journal of Educational Technology*, 55(1), 10-33. https://doi.org/10.1111/bjet.13334

Zhong, C., & Kim, J. B. (2024). Teaching Case: Teaching Business Students Logistic Regression in R With the Aid of ChatGPT. *Journal of Information Systems Education*, 35(2), 138-143. https://doi.org/10.62273/DYLI2468

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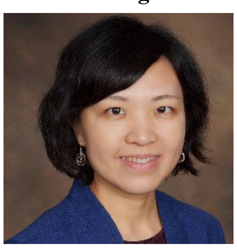

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APPENDICES

Appendix A. Descriptive Statistics of Importance-Performance Analysis

	Importance		Performance	
Dimensions and items	Mean	Std. dev.	Mean	Std. dev.
Perceived ease of use (PE)				
The chatbot is easy to use (PE_1).	4.47	0.69	4.40	0.69
It is well integrated with the course (PE_2).	4.22	0.87	4.04	0.95
It is interacted with understandably (PE_3).	4.40	0.73	4.23	0.83
Perceived usefulness (PU)				
The chatbot improves my course performance (PU_1).	3.91	0.98	3.85	0.99
It provides very useful course information (PU_2).	4.40	0.78	4.24	0.88
It helps increase my course productivity (PU_3).	3.93	0.96	3.81	1.02
It helps enhance my learning effectiveness (PU_4).	4.08	0.91	3.92	0.95
Actual user experience (AE)				
The chatbot answers queries quickly (AE_1).	4.48	0.69	4.39	0.81
It answers queries completely (AE_2).	4.37	0.78	4.16	0.87
It answers queries precisely (AE_3).	4.32	0.83	4.08	0.90
It provides answers that are easy to extract (AE_4).	4.46	0.73	4.21	0.80

Note. Std. dev. = standard deviation.

Appendix B. Discriminant Validity Matrix for the Measurement Model

	PE	PU	AE	AU	LI	EE	PO
PE	**0.76**						
PU	0.66	**0.87**					
AE	0.72	0.54	**0.82**				
AU	0.62	0.57	0.57	**0.89**			
LI	0.64	0.84	0.59	0.73	**0.81**		
EE	0.65	0.70	0.50	0.72	0.77	**0.89**	
PO	0.58	0.76	0.56	0.69	0.75	0.83	**0.85**

Note. PE = perceived ease of use; PU = perceived usefulness; AE = actual user experience; AU = attitude toward using; LI = learner-content interaction; EE = emotional engagement; PO = perceived learning outcomes.

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