EXPLORING THE ROLE OF ARTIFICIAL INTELLIGENCE (AI) IN TERTIARY EDUCATION: STUDENTS' PERSPECTIVES ON NON-HUMAN LECTURERS

LOH YI WEN

BACHELOR OF INTERNATIONAL BUSINESS (HONOURS)

UNIVERSITI TUNKU ABDUL RAHMAN

FACULTY OF ACCOUNTANCY AND MANAGEMENT
DEPARTMENT OF INTERNATIONAL BUSINESS

DECEMBER 2023

EXPLORING THE ROLE OF ARTIFICIAL INTELLIGENCE (AI) IN TERTIARY EDUCATION: STUDENTS' PERSPECTIVES ON NON-HUMAN LECTURERS

BY

LOH YI WEN

A final year project submitted in partial fulfilment of the requirement for the degree of

BACHELOR OF INTERNATIONAL BUSINESS (HONOURS)

UNIVERSITI TUNKU ABDUL RAHMAN

FACULTY OF ACCOUNTANCY AND MANAGEMENT
DEPARTMENT OF INTERNATIONAL BUSINESS

DECEMBER 2023

Copyright @ 2023

ALL RIGHTS RESERVED. No part of this paper may be reproduced, stored in a retrieval system, or transmitted in any form or by any means, graphic, electronic, mechanical, photocopying, recording, scanning, or otherwise, without the prior consent of the authors.

EXPLORE THE ROLE OF ARTIFICIAL INTELLIGENCE (AI) IN TERTIARY EDUCATION: STUDENTS' PERSPECTIVES ON NON-HUMAN LECTURERS.

DECLARATION

I hereby declare that:

(1) This undergraduate FYP is the end result of my own work, and that due acknowledgementhas been given in the references to ALL sources of information be they printed,electronic, or personal.

(2) No portion of this FYP has been submitted in support of any application for any other degree or qualification of this or any other university, or other institutes of learning.

(3) Sole contribution has been made by me in completing the FYP.

(4) The word count of this research report is 10386.

Name of student:	Student ID:	Signature:
LOH YI WEN	2005789	

Date: 29-11-2023

ACKNOWLEDGEMENT

I am immensely grateful for the invaluable guidance and support extended to me throughout my academic journey, especially during my research. It is with profound appreciation that I extend my thanks to my supervisor, Dr Low Mei Peng, whose unwavering encouragement, and expertise have been instrumental in shaping my research endeavors. Her guidance went beyond academic insights; her mentorship fostered an environment where I could explore, learn, and grow. Her patience and dedication in providing constructive feedback not only improved the quality of my project but also honed my research skills significantly. I am truly fortunate to have had such a resolute and supportive supervisor.

I would also like to thank Dr Seah Choon Sen, the second examiner, for his comments and suggestions on my presentation, which was a precious and rare opportunity for me. His suggestions and modifications made my research report completer and more perfect.

Furthermore, I wish to express my sincere gratitude to the Universiti Tunku Abdul Rahman (UTAR) for providing the platform and resources that allowed me to undertake this research journey. UTAR's commitment to academic excellence and research opportunities has been pivotal in shaping my academic pursuits.

I am also indebted to the university students who generously participated in my study, sparing their time and insights. Their contributions were indispensable in shaping the outcome of my research. Their willingness to fill out the forms and share their perspectives added depth and credibility to my findings.

The culmination of my research would not have been possible without the collective support, encouragement, and resources provided by my lovely supervisor, UTAR, and the respondents. I am profoundly grateful for their invaluable contributions to my academic and personal growth.

DEDICATION

This work done is especially dedicated to:

Dr. Low Mei Peng

and

To my families and my loved ones,

Thanks for being there when I needed you the most.

EXPLORE THE ROLE OF ARTIFICIAL INTELLIGENCE (AI) IN TERTIARY EDUCATION: STUDENTS' PERSPECTIVES ON NON-HUMAN LECTURERS.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

AI	Adjusted goodness-of-fix index
KBAI	Knowledge-Based Artificial Intelligence
ITS	Intelligent Tutoring System
AIEd	Artificial Intelligence in Education
TAM	Technology Acceptance Model
FATE	Fairness, Accountability, Transparency, and Explain ability
PU	Usefulness
PEU	Ease of Use
BI	Behavior Intention
PLS-SEM	Partial Least Squares Equation Modelling
CR	Composite Reliability
AVE	Average Variance Extracted
HTMT	Heterotrait-Monotrait Ratio of Correlation
VIF	Variance Inflation Factor
R2	R-squared

LIST OF APPENDICES

PREFACE

The study is conducted as part of course requirements for the Degree of Business Studies (International Business) program in Universiti Tunku Abdul Rahman (UTAR).

The objective of this research being conducted is to EXPLORE THE ROLE OF ARTIFICIAL INTELLIGENCE (AI) IN TERTIARY EDUCATION: STUDENTS' PERSPECTIVES ON NON-HUMAN LECTURERS.

In fact, the study aims to examine the students' perception towards AI teaching and how it relates to students' attitudes in AI based education context. The Technology Acceptance Model by Davis (1995) is referred in this study. Quantitative approach is used to collect data from the tertiary institution students through purposive sampling technique. The targeted sample size is 250 responses for meaningful statistical analysis. Structural Equation Modeling (SEM) technique is used to testifying the proposed hypothesis.

ABSTRACT

AI digital technology is moving forward at a breakneck pace and shows no signs of slowing down. Through surveys of university students, AI technology is already helping today's education systems work smarter.

In today's global education system, not only are our learning models becoming smarter and more efficient, but the adoption of AI Lecturers and the attitudes of university students towards using AI Lecturers have greatly increased. We are becoming more efficient in our learning patterns. AI technology has become an influential factor in our education system.

The main purpose of this study is to determine the relationship between ease of communication, perceived usefulness, attitude toward using AI Lecturers, intention to adopt AI Lecturers and university students' attitude toward AI. The two variables are based on the TAM framework created by Davis (1989). One variable adopts the FATE framework created by Kim et al. (2021). In this study, researchers chose quantitative research design to collect data. A total of 252 responses were received and analyzed. The results of this study show that AI technology is positively correlated with the intention of university students to adopt AI teachers in the education system. In addition, the results of this study also suggest that university students adopt AI teachers on the basis that the ease of communication is minimal.

CHAPTER 1: RESEARCH BACKGROUND

1.1 Technologies in education

Technological development has significantly influenced teaching management, education innovation, and the study of learning behaviour. The advancement in technology and information communication technologies over time has facilitated the creation of artificial intelligence (AI). The growth of deep learning, speech recognition, and natural language understanding has drawn educators' attention to AI technologies. AI has been defined as the use of computers to simulate human minds to carry out cognitive tasks such as thinking, learning, and problem-solving (Wang et al., 2021). Furthermore, the ability of robots to solve problems, reply to queries, formulate strategies, adapt to unfamiliar situations, and do a range of other tasks that require a level of intellect typically found in humans is known as AI.

According to Kim et al. (2020), Jill Watson, the first AI teaching assistant, was introduced in 2016 at Georgia Institute of Technology in the United States by Professor Geol. This AI teaching assistant was initially created for the professor's online Knowledge-Based Artificial Intelligence (KBAI) course. The IBM Watson platform was used to create the AI teaching assistant, which was largely created to respond to comments made by students in the online discussion boards for the KBAI course. When the professor revealed the teaching assistant's identity at the end of the semester, several students were curious about her due to her swift responses.

Subsequently, AI has been positioned as having grown strategic advantages for education. AI could be a helpful educational tool that lessens the responsibilities of teachers and students while giving them interesting learning possibilities. With contemporary educational reforms including the digitalization of educational resources, gamification, and personalised learning experiences, there are enormous opportunities for the development of AI applications in education. One method of creating reactive and adaptive tutorials for creating customised learning environments using an intelligent tutoring system (ITS) is to systematically exploit the modelling capabilities of AI approaches (Zhai et al., 2020).

According to Sun et al. (2020), the most current point to attracts educational sector focuses on new teaching approaches that support educational professional development and deliver the best courses on each subject that attract students' attention. AI supports and teaches an environment of global education devoid of bias. By learning outside of the classroom, technology will be improved for the rest of a person's life. Greater worldwide interconnection and accessibility result from the classrooms' global launch. To develop intelligent teaching programs, AI is essential in monitoring learners' mental behaviours such as self-regulation, control, and description. This determines the information that is most appropriate for the learner. AI supports transforming training and practice in comprehending into complex thinking and learning processes. The growth of technology use across all industries has had a huge impact on how education students benefit from an exciting learning experience when technology is used in the classroom, which helps them focus on the material longer.

Student learning can be made more dynamic and engaging by developing activities in the classroom that integrate technology resources, oral presentations, and group interaction. Verbal exchanges are not the only kind of participation (Haleem et al., 2022). Additionally, the increasing use of technology in all sectors of the economy has had a significant impact on how education is delivered and how people are educated about it. By substituting tablets and e-books for traditional textbooks, students may have greater access to quickly updated content. Active teaching techniques that make use of technology to enhance learning have taken the place of earlier methods. These strategies increase learner engagement and support the concepts of self-directed, immersive, relevant, and problem-cantered adult learning (Altmiller et al., 2022). Artificial intelligence (AI) has also been heavily utilised in the education sector, in accordance with the adoption and application of new technology in education.

1.2 AI in education

To encourage innovation and improve productivity, artificial intelligence (AI) is being used in increasing numbers in a range of industries, including banking, education, and industry. In the realm of education, AI is seen as an ostensibly all-powerful tool that may supplement or even replace teachers' efforts by automatically tracking students' growth, assessing their performance, and providing them with tailored guidance. Teachers may depend on AI to help

them make educated decisions about how to organize their instruction to better assist student learning (Wang et al., 2023). According to Luckin et al. (2016), artificial intelligence in education (AIEd) provides the opportunity for learning that is more individualized, adaptable, inclusive, and interesting. It can provide teachers and students with the tools they need to address both what is being learnt and how it is being learned, as well as the feelings of the students. It can help instructors create more sophisticated learning environments than would otherwise be possible, and it can help students acquire the skills and information that employers appreciate. Additionally, AIEd may promote collaborative learning by ensuring that the right group is constituted for the job at hand or by providing targeted support at precisely the right time, both of which can be difficult for one teacher to achieve alone.

Nowadays, understanding how to learn is given a lot of attention. It provides the foundation for lifelong learning, which is now more important than ever. It might be argued that self-direction and lifelong learning are interdependent and serve as the foundation for each other because most researchers e.g., Tekkol and Demirel identify a link between them. Setting goals that can be measured in both concrete and abstract terms, managing short-term and long-term goals and time, planning carefully, and working quickly are all examples of how learners show self-direction. Working independently is critical to achieving learning objectives, in addition to managing time and goals. This means taking the initiative to learn more, extend perspectives, and critically consider the impact of the past on the present (Kurent & Avsec, 2023).

The fast growth of computing technology and the rising demand for a variety of learning settings are fundamentally related to the smooth growth of higher education. AI technology can provide superior knowledge to improve the growth of students' knowledge and the real-time evaluation of the school to better understand the impact of student learning. The strong AI computing framework has a significant impact on a lot of the current educational environment. AI is gradually changing the school's all structure, bringing about an intelligent teaching-learning platform, and improving assessment. It is important to note that artificial intelligence's "machine learning" is a promising technology with the potential to learn patterns and predict innovation in the educational environment (Hu, 2023).

Furthermore, a type of collaboration or solution that can help disabled people worldwide is human-AI interaction. These technologies can inspire people to take advantage of AI in higher education. It can inspire students and teachers to become more actively involved in the teaching and learning process. Administration, instruction, and learning have all been combined with AI

in education (Fahimirad et al., 2018). According to Ahmed et al. (2022), higher education might benefit a lot from AI, including but not limited to the following: on-demand curriculum customization; personalized student engagement; interactive teaching and smart content; better learning outcomes; and reduced administrative workload. The use of AI in educational settings has recently grown across the world. Nowadays, teachers employ AI in many different contexts. There will be a 43% rise in students using AI by 2022 (Ahmed et al., 2022). Students can feel socially connected to their teacher, which is proof that they can form social views of the educator based on the accessible indicators of whether they converse with the teacher in a physical classroom. In this regard, the study explores whether the social presence of a human teacher that students have already experienced aids them in developing certain expectations about a machine teacher who they would not personally encounter but who would fulfil a similar role to a human teacher (Kim et al., 2022).

1.3 Research Problem

AI technology is receiving attention and is constantly being developed. So does its application in education. This will considerably increase the effectiveness of teaching and provide students with logical ideas. Luckin and Holmes (2016) claim that they had an argument about AI's place in the classroom. There are still plenty of challenges with technology integration in education. The optimal interaction between humans and computers is still a long way. AI tools and technologies are still used in education today. A comprehensive intelligent teaching system must incorporate education, psychology, and other fields in addition to relying on the continuous advancement of AI technology. Whether AI education can be rapidly incorporated into the educational system will depend on how it affects students and how the students respond. Since there has not been enough comprehensive study on the use of AI in education, the current tools for AI are mostly used in exam-oriented educational systems. The phenomena on hand have motivated this study.

1.4 Research Questions and Objective

Research Question:

The rapid advancement of technology has greatly impacted how people communicate, treat illness, and learn. Focusing on educational institutions, information technology has had a significant, if occasionally gradual, impact on all present teaching and learning processes. There is no obvious improvement in how teaching and learning are now carried out because of technological innovation in education (Roy et al., 2022). When former Higher Education Minister Datuk Seri Idris Jusoh emphasised the topic of "Higher Education 4.0: Knowledge, Industry, and Humanity" in 2018, the trend towards education 4.0 in the Malaysian educational system got its start. He thinks that the inclusion of IR4.0 in the higher education system in Malaysia will assist the educational institutions maintain their relevance and competitiveness as Industry 4.0 begins to take hold. Higher education institutions are under pressure to reform their curriculum and implement teaching and learning 4.0 initiatives (Halili, 2019). The theory of the Technology Acceptance Model (TAM) is considered appropriate as the theoretical framework for this study that university students' intention to embrace AI lecturer plays a crucial role in participation, consumption, and adoption.

Specific Research Questions:

- What is the university students' perceptions toward the adoption of AI lecturer?

-How does the perception of an AI lecturer's usefulness affect the perception of its adoption by university students?

-How does the perception of adopting an AI lecturer among university students depend on how simple communication with an AI lecturer is?

-How does student perception of adopting an AI lecturer among university students depend on attitude towards employing an AI lecturer?

Research Objective:

Following the above-mentioned research questions, below are the objectives of this study:

(1) To investigate the relationship between students' perception toward AI and perception to adopt AI lecturer among university students;

(2) To investigate the relationship between perceived usefulness of an AI lecturer and perception to adopt AI lecturer among university students;

(3) To investigate the relationship between ease of communication with AI lecturer and perception to adopt AI lecturer among university students;

(4) To investigate the relationship between attitude toward using AI lecturer and perception to adopt AI lecturer among university students.

1.5 Research Significance

Cutting-edge technologies in the area of "AI with education" such as educational knowledge graphs, cognitive diagnosis, learner modelling, machine reading comprehension, and marking are continuously emerging as a result of the technological advancement of AI in the field of education. The educational knowledge graph expresses all varieties of real-world knowledge into a structure that can be computer-stored and calculated. The knowledge graph is created by cantering on knowledge points, courses, teaching, and resources. This method not only makes it possible to analyse a single entity type, such as knowledge points, courses, and resources, but it also allows for analysis of the overall correlation and influence of various teaching-related factors. Cognitive diagnosis uses big data and artificial intelligence analysis technology to make up for the shortcomings of traditional cognitive models of education. However, students are a key factor in the success of AI education. Students are the direct users of AI education, and their attitude towards and acceptance of AI education will directly affect the

popularization rate of AI education. That is also the purpose of the study. The finding from this study will help HEIs to make better planning and revision in pedagogy.

1.6 Conclusion

This chapter provides an overview of the development of AI and AI in education.

CHAPTER 2: LITERATURE REVIEW

2. Literature Review

The literature review chapter presents theory, independent variable, dependent variable, and framework. The theories are Fairness, Accountability, Transparency, and Explain ability (FATE) and Technology Acceptance Model (TAM). The independent variable are student's attitudes toward AI, perceived usefulness of an AI lecturer, ease of communication with AI lecturer, and attitudes towards using AI lecturer. The dependent variable is the intention to adopt AI lecturer.

2.1 Theory

2.1.1 Fairness, Accountability, Transparency, and Explain ability (FATE)

Research to date shows that a machine teacher is "a technology that plays a meaningful role during an interaction with humans in helping them engage in affective, cognitive, and behavioural learning through various ways," according to the definition given by the researchers. Machine teachers can take many different forms. For instance, virtual presence robots and social robots like Pepper can be employed successfully in a face-to-face educational setting. In an online learning environment, virtual agents such as chatbots and software agents can interact via text or speech (Kim et al., 2022).

According to Kim et al. (2021), different methods, including embodied and ethereal forms, are possible for machine teachers to come into being. Embodied machine teachers are employed in a variety of educational settings. Embodied agents are developed with a physical instantiation or a physical body. For instance, telepresence robots are used at the Saatchi Gallery in London to conduct online educational sessions about the artworks and sculptures on display. Researchers began examining the effectiveness of embodied machine teachers in comparison to human teachers after acknowledging the emergence of embodied agents in education. Students' perceptions of a robot evaluator for public speaking skills were compared to those of a human evaluator in the study (Edwards et al., 2021). Both evaluators obtained favourable ratings that are above the midpoint of the evaluation scales, with students reporting more positive evaluations and social impressions of a human evaluator than a robot evaluator, such as attraction and social presence.

Sony AIBO and NAO robots are two examples of physically embodied machines that have been employed in face-to-face learning situations. These computer-generated individuals with recognisable bodily forms that only exist on screens are known as virtually embodied machine teachers. A virtual assistant that is presented in the form of an animated figure includes Clippy, a smart user interface that helped users through an interactive animated character in the early days of Microsoft. It's also feasible to create a hybrid form of machine teachers that blends actual and virtual agents. To put it another way, some robots with physical forms have electronic tablets that show virtual agents with real-world forms on a screen (Kim et al., 2020). It's significant that Kim et al. (2021) underlines the value of social presence. Comparatively speaking to a functional AI teacher, a relational AI teacher promotes a stronger social presence, which in turn supports positive impressions of the AI teacher. The availability of these programmes, which institutions ought to adopt initially, impacts whether students want to pursue an education based on AI.

Kim et al. (2021), highlight that adopting an AI-based education successfully requires building positive opinions of a machine agent considering the possibility of such availability in the future. Given the growing demand for and popularity of online courses in higher education, machine teachers are expected to be in high demand soon (Allen & Seaman, 2017). Given the characteristics of an online environment, it is extremely likely that detached, or virtually embodied computer teachers will be

required. It is unclear how students could react to the idea of robot lecturers, though. The current study examines how children perceive machine teachers through the theoretical lens of the Technology Acceptance Model (TAM).

2.1.2 Technology Acceptance Model (TAM)

Davis (1989) developed the Technology Acceptance Model (TAM) to predict and explain the factors that encourage consumers to adopt and employ new information technology systems. TAM was chosen as the paradigm for e-government technology adoption in this study. Its primary strength is that it is a general model that may be used in any ICT-based scenario, to start. Its capacity to predict the adoption of information systems has also gained extensive validation, applications, and replications (Nguyen, 2023).

To understand attitudes and behavioural intentions in connection to the usage of new technologies, TAM focuses on two categories of personal beliefs, usefulness (PU), and ease of use (PEU). The degree to which a person thinks using a particular system would enhance his or her quality of life or professional performance is known as usefulness (ElKheshin & Saleeb, 2020). According to Al-Adwan et al. (2023), the TAM model was created to identify the psychological and cognitive variables that affect users' acceptance of new technology. According to TAM, technology adoption and use (Actual Behaviour) are determined by behaviour intention (BI). Additionally, people's attitudes towards technology use (A) and their estimation of its utility (PU) are "jointly determined" by behaviour intention. As a result, people's attitudes are influenced by how useful they think something to be and how simple they believe it to be to use. Both PU and PEU are determined by external factors. Due to the external variable architecture, TAM enables researchers to incorporate other potential factors that could influence the adoption of a certain technology.

The TAM has been applied in educational environments to comprehend e-courseware, e-Portfolios for learning, educational wikis, and social media for learning. All this

research emphasise the impact perceived utility and perceived usability have in adopting educational technology in a few different ways, like previous studies that employed the TAM (Kim et al., 2020). For instance, a study (Abdullah et al., 2016) discovered that a person's behaviour might be influenced by a student's perceptions of the utility and usability of e-portfolios. To understand the adoption of e-learning, or tools that use internet technology for educational purposes, Abdullah and Ward (2016) performed a meta-analysis utilising the TAM.

Numerous arguments highlighted by Sánchez-Prieto et al. (2019) highlight critical TAM components in teachers' comprehension of AI-driven evaluation. Teachers' intents to employ AI-driven evaluation in eLearning are positively connected with perceived utility and perceived usability, which will ultimately lead to adoption, according to Sánchez-Prieto et al. (2019), who base their argument on the TAM. This research emphasises the theoretical foundations of the TAM in the understanding of educational experiences related to AI, even though they are constrained to conceptual assumptions without any supporting empirical data.

The TAM framework has external components that have been validated based on personal trust and are made up of three dimensions: usefulness, readiness to act, and simplicity of use. However, using TAM as a framework is possible that individuals' willingness to use these technologies may not be entirely determined by their ease of use and usability. As a result, additional variables should be considered to better understand users' impressions on this basis. As one of the theoretical frameworks of an extended research model, TAM was employed in this study to assist explain students' acceptance of and intention to engage in continuous learning through online learning (Ye et al., 2023).

According to Al-Hattami (2023), the TAM model has been used and expanded in many industrialised nations to demonstrate its validity. Expanding the TAM was discovered that self-efficiency and social influence are crucial elements influencing user intention to utilise new technology. This model has not yet undergone extensive testing in LDCs. Furthermore, it is seen as a study fault as most TAM validations have concentrated on university students rather than academics or teachers. TAM is appropriate at various educational levels and in various nations. The importance of confirming the TAM in

various situations and nations was also mentioned in the systematic literature review to support its cross-cultural validity.

2.2 Independent Variables

2.2.1 Student's Attitudes toward AI

Eagly and Chaiken (1993) define attitude as a "psychological tendency, expressed by evaluating a particular entity with some degree of favour or disfavour." According to Tang (2023), AI does have a significant impact on the educational process. However, no research material specifically shows how AI affects the population of college students. Nevertheless, increasing student motivation is a vital strategy for enhancing learning, and active learning has been strongly supported in education and is an important component of constructivist theory. Moreover, according to Suh and Ahn (2022), the TAM considers perceived usefulness, which is "the prospective user's subjective probability that using a specific application system will increase his or her job performance within an organisational context", and perceived ease of use, which is "the degree to which the prospective user expects the target system to be free of effort"; both affect attitude and behavioural intention.

2.2.2 Perceived usefulness of an AI Lecturer

The purpose of behaviour is determined by "Perceived Usefulness," which is influenced by the technology's "Ease of Use" and the user's attitude when using it. According to Davis et al. (1989), "Perceived Usefulness" is the subjective likelihood that a user

would become more productive when using a particular application at work, enabling them to do their tasks more effectively. Furthermore, the TAM takes into consideration perceived usefulness, which Davis et al. (1989) define as "the prospective user's subjective probability that using a specific application system will increase his or her job performance within an organisational context." Perceived usefulness has an impact on user acceptance of computer systems due to the growing value of findings. Users' learning engagement has also been greatly influenced by intelligent teaching environments, system self-efficacy, perceived ease of use, perceived usefulness, and interaction. In a learning environment when new technology is used, students' perceptions of its value, their behavioural objectives, and their satisfaction may have an impact on how effective the new technology (Wang et al., 2021).

2.2.3 Ease of communication with AI Lecturer

Since this serves as the foundation for a system's use, the latent variable "Ease of Use" is crucial to acceptance of an information system. The perceived 'Ease of Use' relates to how much the potential user expects that using the system will be effortless. A user will likely stop using a system that they find difficult to operate since they will think it is less useful (Davis, 1989). According to TAM Theory, which claims that a customer will feel that utilising online banking can be useful when the usage is also easy for them, there is a considerable association between perception of ease of use and perception of benefits (Muchran and Ahmar, 2019). Considering that most communication is scripted, AIs might readily and successfully supplement lectures in online learning environments. Although the fact that AI lecturers may not be fully embraced in educational settings for some time, the trend appears to be in this direction (Kim et al., 2021).

2.2.4 Attitude toward using AI Lecturer

Nowadays definition of attitude is a "psychological tendency, expressed by evaluating a particular entity with some degree of favour or disfavour" (Eagly & Chaiken, 1993). Positive attitudes towards using a particular technology and its perceived usefulness, according to Davis et al. (1989), are directly related to a person's behavioural intention to use the technology, which would influence a person's actual behaviour in embracing the new technology. Furthermore, by utilising a new system or technology, it has been shown that user attitude has a significant, direct, and favourable impact on the true consumer intentions. According to Schepman and Rodway (2020), technology acceptance is a concept that primarily focuses on the consumer's willingness to adopt technology. However, user choice is frequently not taken into consideration in the use of AI because big organisations and governments may decide to implement AI without engaging its end users, leaving them with no choice but to interact with it.

2.3 Dependent Variables

2.3.0 Intention to adopt AI Lecturer

According to the TAM model, the purpose to engage in a specific action, such as using a technology, determines how people utilise technology. The purpose and other elements influencing a user's behaviour can be used to forecast how they will utilise a technology (Davis, 1989). Moreover, the importance of social presence is highlighted by Kim et al. (2021). That is compared to a functional AI instructor, a relational AI lecturer encourages a stronger social presence; this enhanced social presence therefore supports favourable impressions of the AI lecturer. The availability of such courses, which universities should implement first, determines students' intents to enrol in AI-based education.

2.4 Framework

Figure 1 is the research framework developed to explore the university student's intention to adopt AI lecturer. The student's attitudes toward AI lecturer are dependent on the perceived usefulness of AI lecturer and ease of communication with AI lecturer. Those reason will affect the student's attitude toward using AI lecturer. This will cause the university student to have the intention to adopt AI lecturer.

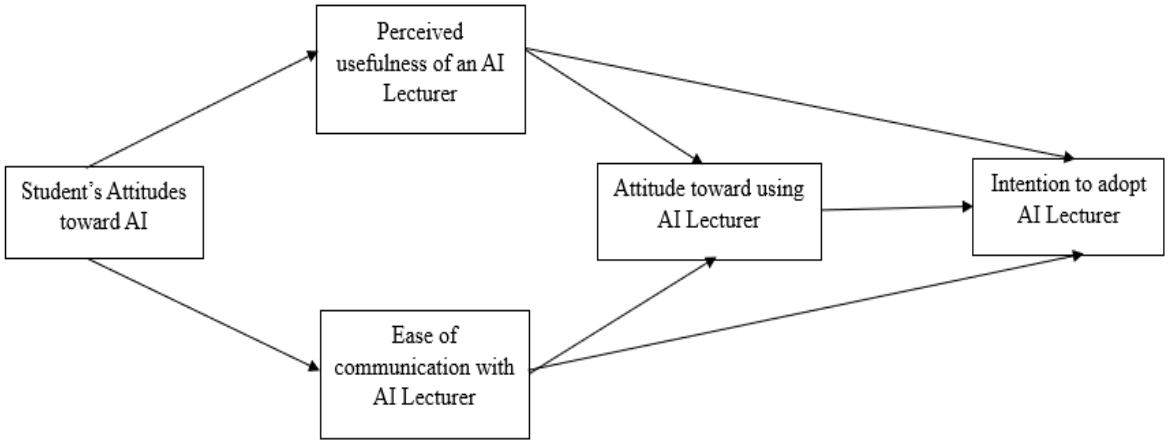


Figure 1 Research framework

2.5 Hypotheses Developments

H1: Student's attitudes towards AI have a positive relationship on perceived usefulness of AI Lecturer.

H2: Student's attitudes towards AI have a positive relationship on perceived ease of communication of AI Lecturer.

H3: Perceived usefulness has a positive relationship on attitude towards AI Lecturer.

H4: Ease of communication has a positive relationship on attitudes towards AI Lecturer.

H5: Perceived usefulness has a positive relationship on intention to adopt AI Lecturer.

H6: Ease of communication has a positive relationship on intention to adopt AI Lecturer.

H7: Attitudes towards AI Lecturer has a positive relationship on intention to adopt AI Lecturer.

2.6 Conclusion

This chapter describes the Machine teacher and TAM model theory, review of variables used to support the research framework. Furthermore, the research framework is created to investigate the link between the variables. Moreover, hypotheses are developed based on a thorough assessment of the literature. The following Chapter 3 will cover the research technique utilised to conduct this study.

CHAPTER 3: RESEARCH METHODOLOGY

3. Research Methodology

Research methodology is the study of the techniques used in scientific inquiry. a plan for logically fusing different approaches to tackle the research problem. By using technique, scientific research outcomes and the process itself are better understood. In order to link these potentialities to the "frontiers of knowledge" liminal area, research methodology aims to explain and evaluate procedures, emphasise their strengths and flaws, and make these weaknesses and assumptions obvious (Patel & Patel, 2019). As a result, the research design, sampling design, data collection techniques, and suggested data analysis tool will all be explained in this part.

3.1 Research Design

Research design refers to how a researcher sets up the methodologies and techniques they use to handle a research problem. This includes the study question, objectives, hypotheses, variables, samples, choice of data gathering techniques, and techniques for data analysis (Ishtiaq, 2019). The strategy for answering the study's guiding research questions is known as the research design. The preparation and execution of the investigation in a method that would yield the intended results is aided by designing a research as well. This increases the possibility of finding out information about the true situation.

3.1.1 Exploratory Study

Exploratory research investigates topics that haven't been studied before and request a more detailed explanation. Exploratory research doesn't aim to conclude, but rather a thorough grasp of the problem. Exploratory research is frequently carried out to better understand the nature and underlying causes of an issue when a problem is not identified. The heart of good research, according to the explanation, is an exploratory study. Research would stop if there was no desire to present something new. Non-exploratory research can only confirm existing knowledge. This won't advance science, except from replication-focused studies (Swedberg, 2020). The problem with this definition of exploratory study is that it becomes exceedingly broad and difficult to manage. The idea that research should always aim to say something new is crucial, but it will only take far. When the expression "exploratory study" is used in this context, it also tends to be used to refer to everything that is thought to be "good research" as well as everything that has contributed to this conclusion. This implies a huge amount of literature that already addresses a wide range of subjects (Swedberg, 2020).

3.1.2 Quantitative Research Design

Quantitative research tries to explain phenomena by the gathering of numerical data and its analysis using mathematically based methodologies, particularly statistics. Quantitative research is controlled, rigorous, objective, and goal-oriented since it aims to quantify the variance of a certain condition, problem, event, or occurrence. Quantitative research aims to discover and apply mathematical theories, models, and/or hypotheses that are pertinent to phenomena. To understand human behaviour and social events, quantitative research entails the systematic collecting and analysis of numerical data. It is often used to explore relationships between variables and test hypotheses. Quantitative research is more structured and objective than qualitative research (Kandel, 2020). This study uses a questionnaire survey, and it is quantitative.

3.2 Sampling Design

3.2.1 Target population

This study focuses on current university students in Malaysia. A few requirements must be met by every respondent to achieve the goals and improve the reliability of the research. Respondents must meet the following requirements: they must be Malaysian nationals, be enrolled at university presently, and be in the first to fourth semesters. In order to collect data, the study will utilise a quantitative methodology in which questionnaires will be developed and sent to Malaysian university students. An online survey using Google Form has been used to all potential respondents have access and to enhance the chance that the survey will reach the intended respondents. To be completed by the respondents using a Google form, a total of 250 questionnaires have been distributed.

3.2.2 Sampling techniques

Sampling is a technique that researchers employ to methodically select fewer, more representative objects or individuals from a pre-defined population to serve as subjects for observation or testing in line with their study goals (Sharma, 2017). Non-probability sampling will be used in this study to identify the factors that influence academic success. Non-probability sampling allows for bias in the selection of participants based on the kind of person who would choose to take part in an online survey. Any survey research will be subject to selection bias, and it is up to the researcher to accept or mitigate its effects. Just as specific people will be drawn to joining an online panel, a certain type of person is willing to respond to a phone survey or a mail survey (Lamm & Lamm, 2019). In this investigation, the sampling strategy was non-probability sampling. Non-random population sampling typically employs the non-probability technique known as convenience sampling. For several different reasons, convenience sampling refers to the selection of study subjects based on their accessibility to the

researcher. This straightforward sampling technique is widely used for fast market analyses or election forecasting.

3.2.3 Sample Size

In many research fields, sampling to estimate the population mean is a common problem (Rogers et al., 2020). More than 30 respondents and less than 300 respondents have been indicated as the most suitable sample size (Sekaran et al., 2003). To the target population, which consists of Malaysian university students, 250 sets of questionnaires were provided.

3.3 Data collection method

In research initiatives, gathering data can be delicate, thus it must be done appropriately, from reliable sources, and according to established procedures (Mkandawire, 2019; Heath et al., 2018). Data collection is defined as the methodical process of gathering information required to solve a particular research issue, develop a response to a research question, or act as a basis for the approval or rejection of research hypotheses. This suggests that if done incorrectly, it can fail to address research-related concerns and, ultimately, fail to answer research-related questions. As a result, selecting a method or tool for gathering data is one of the most important choices a researcher must make (Heath et al., 2018). Data collection methods are the techniques, tools, or processes that researchers use to collect data for their research topics. Most of the time, data collection occurs in the field; however, on occasion, it also occurs in other places, such as libraries, historical archives, and other online sources (Mwita, 2022). It consists of both primary data, which is information acquired directly from original sources, and secondary data, which is information gathered from sources that already exist but received processing and analysis. For the data to be valid and reliable, the techniques employed to collect them must be in line with the design of the study and the choice of samples. Typical methods of gathering data

include surveys, interviews, experiments, and observations. We will utilise questionnaires in this study because they are a common method of collecting data from participants. It can be used to find out what the pupils thought and felt. The primary methods used in this study.

3.3.1 Primary Data

Primary data is information that a researcher initially collects from reliable sources. Only research techniques including interviews, questionnaires, focus groups, and observation are allowed for gathering primary data (Mwita, 2022). This type of data collection entails the gathering of information through a variety of techniques, such as surveys, interviews, observation, and experiments. For researchers, primary data is essential since it offers precise, trustworthy, and current information about a particular research issue. However, gathering primary data requires the creation of data collection tools, the development of a research strategy, and the collection and analysis of data, which can be costly and time-consuming. To ensure that the main data is correct, objective, and pertinent to the research objectives, the researcher must also have the necessary skills and knowledge. Despite these difficulties, primary data is thought to be the most trustworthy and accurate data source since it offers unique and comprehensive viewpoints on the research issue that are unavailable from secondary data sources. Survey questionnaires will serve as the foundation for our data collection project. While questionnaires are self-administered surveys that respondents fill out themselves, surveys involve distributing a set of standard inquiries to a sample of respondents. This approach gives you a lot of control over the data you collect, ensuring that it's relevant to the purposes of the study.

3.4 Methods of Analysis

To study the factors influencing Malaysian university students' perception of non-human lecturers, data from primary sources will be merged. Statistics is the cornerstone of data analytics. Users can spot patterns and trends in most numerical data thanks to the study of mathematics. The two types of statistical techniques are descriptive statistics and inferential statistics.

3.4.1 Description Statistics

Descriptive statistics can be used to summarise data visually with histograms and box plots as well as simply quantitative measurements like percentages or means. Descriptive statistics can be used to characterise a single variable (univariate analysis) or several variables (bivariate/multivariate analysis). Descriptive statistics can help summarise associations between variables when there are several variables by using tools like scatter plots (Kaliyadan & Kulkarni, 2019). Initial data analysis must include descriptive statistics because they form the foundation for inferential statistical tests that compare variables. To reduce the likelihood of providing erroneous results, it is necessary to report the most relevant descriptive statistics using a systematic approach (Kaur et al., 2018).

3.4.2 Inferential Statistics

According to Sheard (2022), although it has been around for a while, interpretive analysis is frequently dispersed among several analysis positions and does not appear

to have a well-known or recognized "brand name." By using sample data, inferential statistics refers to drawing inferences about the traits of the wider population that the sample is meant to represent (Urdan, 2022). Inductive statistics is another name for inferential statistics. The application and significance of inferential statistics are both expanding. Research on medicines is one area where inferential statistics are used. Tests on new medications must be restricted to small patient samples since some new medications are expensive to create. Researchers can organize studies with tiny, randomly chosen patient samples using inferential statistics to draw findings and draw assumptions about the population (Black, 2023).

3.5 Partial Least Squares Equation Modelling (PLS-SEM)

In PLS-SEM, composite variables are created by linearly combining the model estimates of indicators from a measurement model. The composite variables are trusted replacements for the conceptual variables under discussion since they are thought to be complete representations of the constructs (Hair & Sarstedt, 2019). However, this does not mean that PLS-SEM can only estimate constructs that have been specified in a formative manner. The composite-based approach is in line with the measurement theory that supports formative measurement. Therefore, while constructing composites to represent conceptual variables, it is crucial to distinguish between the estimate perspective and the measurement theory perspective. The way a method like PLS-SEM estimates the model parameters must be distinguished from any measurement theoretical considerations for operationalizing constructs. Researchers can use measurement models that are simply estimated by PLS-SEM and are reflectively and formatively specified (Hair et al., 2021).

3.6 Measurement Instrument and Measurement Scale

Construct	Measurement Items	Scale	Source
Student's Attitudes toward AI *(Cognitive components)*	1. I think that teaching students about AI in the classroom is important. 2. AI class is important. 3. I think AI courses need to be taught in schools. 4. In my opinion, all students should study AI in school.	1 = Strongly Disagree, 7 = Strongly Agree	Suh and Ahn (2022)
Student's Attitudes toward AI *(Affective components)*	5. AI is necessary for the development of society. 6. In my opinion, AI makes life easier for people. 7. AI has a connection to my life. 8. I will use AI to find solutions for problems that I face every day. 9. AI helps me in real-world problem-solving. 10. In the future, AI will be essential to my life. 11. Everyone needs AI. 12. AI produces more benefits than drawbacks. 13. AI needs further investigation. 14. In my opinion, most careers in the future will require knowledge of AI.	1 = Strongly Disagree, 7 = Strongly Agree	Suh and Ahn (2022)
Student's Attitudes toward AI *(Behavioural components)*	15. The field of AI is the place I want to work. 16. I will choose a position in the AI industry. 17. If there were a club about AI, I would join it. 18. I enjoy employing AI-related objects. 19. Learning about AI is enjoyable. 20. I wish to keep learning more about AI.	1 = Strongly Disagree, 7 = Strongly Agree	Suh and Ahn (2022)

	21. I am interested in watching videos online on AI. 22. Using AI, I want to create something that makes life easier for people. 23. The development of AI interests me. 24. The use of AI is interesting. 25. There should be more time spent discussing AI in class. 26. I am knowledgeable about AI.		
Perceived usefulness of an AI Lecturer	1. My learning experience would improve if I used an AI lecturer. 2. My ability to study more effectively would increase if I used an AI lecturer. 3. My studies would be easier if I have an AI lecturer. 4. I could use an AI lecturer to coach me for my coursework. 5. I could complete tasks faster in my study if I have an AI lecturer.	1 = Strongly Disagree, 7 = Strongly Agree	Davis (1989)
Ease of communication with AI Lecturer	1. With an AI lecturer, learning how to communicate with it would be simple. 2. An AI lecturer wouldn't require much of my mental effort to interact with. 3. My communication with the AI lecturer would be simple and clear. 4. I think interacting with an AI lecturer would be flexible.	1 = Strongly Disagree, 7 = Strongly Agree)	Davis (1989)
Attitude toward using AI Lecturer	1. Utilizing an AI lecturer increases the standard of my study. 2. I have more control over my study when I have an AI lecturer. 3. I can learn more effectively than I otherwise could because of the AI lecturer.	1 = Strongly Disagree, 7 = Strongly Agree)	Davis (1993)

	4. I believe that with some adjustments, the AI lecturer could be even more user-friendly for me. 5. Having an ai lecture can learn more technical skill.		
Intention to adopt AI Lecturer	1. If there was an online course with an AI lecturer, I would consider taking it. **2.** I would be interested in participating in an online course that uses an AI Lecturer.	1 = Strongly Disagree, 7 = Strongly Agree	Choi and Ji (2015)
	3. I intent to register courses with AI Lecturer. 4. I would like to have AI Lecturer as my lecturer. 5. I would recommend to my friends to have AI Lecturer. 6. It is likely that I will register in courses that with AI Lecturer.		Kim et al. (2010)

3.7 Conclusion

An overview of the research methods used in the study is given in Chapter 3. In the subsequent chapter 4, the analysis and interpretation of data will be done and explained thoroughly.

CHAPTER 4: DATA ANALYSIS

4. Data Analysis

One of the most popular techniques for multivariate data analysis among business and social science researchers is partial least squares structural equation modelling (PLS-SEM), sometimes referred to as PLS Path Modelling. Since its rapid development in the early 2000s, PLS-SEM has gained popularity among researchers and students, mostly for examining models containing latent variables (Memon, 2021). This chapter will present the results and analysis the result.

4.1 Responder's Profile

Table 1 reports that most of the respondents are female, accounting for 61.5%, while 38.5% are male. Most of the respondents' education level (94.4%) are degree and 5.6% are postgraduate. For year semester, about 40.1% of respondents are Year 3; 29% of respondents are Year 2; 18.3% of respondents are Year 4; and 12.7% of respondents are Year 1. Private university's respondents (82.5%) are more than public university's respondents (17.5%). There are medical faculty (7.54%), pure science faculty (9.92%), social science faculty (75%), and other faculty (7.54%) which are the respondents are studying. Chinese respondents are dominant among other ethnicities, accounting for 72.6%, followed by Indians (14.3%), Malays (12.3%) and other (0.8%). Regarding the CGPA result 63.9% of the respondents get the result above 3.0, 34.5% get the result 2.0 to 3.0, and 1.6% get the result below 2.0. Around 58.3% of respondents have taken a class taught by a non- human lecturer, and 41.7% have not taken a class taught by non-human lecturer.

Table 1

Profile	Sample (N=252)	Percentage
Gender		
Female	155	61.50%
Male	97	38.50%
Education Level		
Degree	238	94.40%
Postgraduate	14	5.60%
Year Semester		
Year 1	32	12.70%
Year 2	73	29%
Year 3	101	40.10%
Year 4	46	18.30%
Type of University		
Private University	208	82.50%
Public University	44	17.50%
Faculty		
Medical	19	7.54%
Pure Science	25	9.92%
Social Science	189	75%
Other	19	7.54%
Race		
Chinese	185	72.60%
Malay	30	12.30%
Indian	35	14.30%
Other	2	0.80%
Result (CGPA)		
Above 3.0	161	63.90%
2.0 - 3.0	87	34.50%
Below 2.0	4	1.60%
Have you ever taken a class taught by a non-human lecture?		
Yes	105	58.30%
No	147	41.70%

4.2 Measurement Model Evaluation

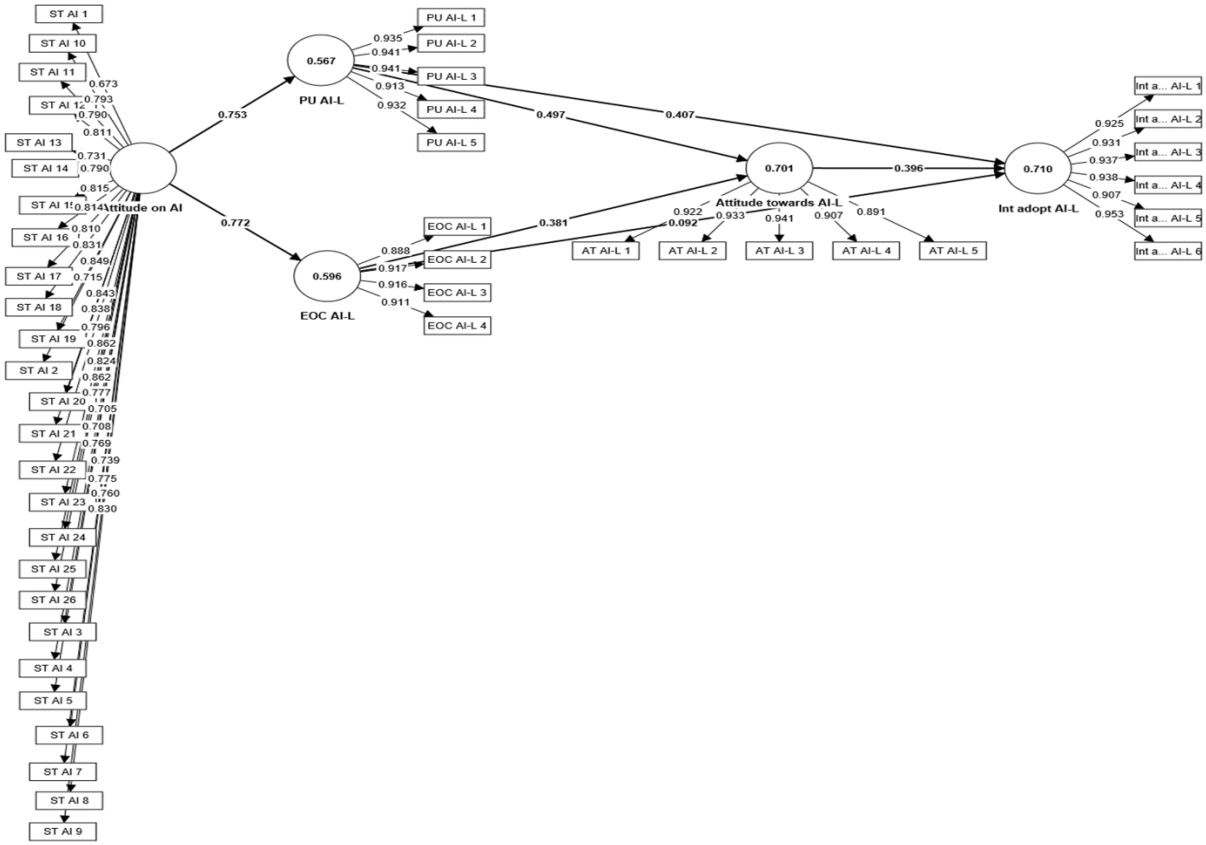
Using PLS-SEM, the conceptual model of this study was examined in two stages. The measurement model evaluation was done in the first stage, and the structural model assessment was done in the second stage. Reflective measurement models should have factor loadings higher than 0.7, composite reliability (CR) greater than 0.7, average variance extracted (AVE) greater than 0.5, and Cronbach's alpha higher than 0.8 (Hair et al., 2019). The results of the reflective measurement model are shown in Table 2 and Figure 2 respectively. Each factor's AVE value was greater than 0.5, and the study accepted it. The criteria of AVE more than 0.5 and CR greater than 0.7 were met by all five constructions. Every construct met the criteria for both convergent validity and reliability.

Table 2 The results of reflective measurement model evaluation

Construct	Items	Factor Loading	Cronbach's Alpha	Composite Reliability (rho_a)	Composite Reliability (rho_c)	Average Variance Extracted (AVE)
Attitude towards AI-Lecturer	AT AI-L 1	0.922	0.954	0.954	0.965	0.845
	AT AI-L 2	0.933				
	AT AI-L 3	0.941				
	AT AI-L 4	0.907				
	AT AI-L 5	0.891				
Ease of communication with AI Lecturer	EOC AI-L 1	0.886	0.929	0.929	0.949	0.824
	EOC AI-L 2	0.918				
	EOC AI-L 3	0.916				
	EOC AI-L 4	0.912				
Intention to adopt AI-Lecturer	Int adopt AI-L 1	0.925	0.970	0.971	0.975	0.869
	Int adopt AI-L 2	0.932				
	Int adopt AI-L 3	0.937				
	Int adopt AI-L 4	0.938				
	Int adopt AI-L 5	0.906				

	Int adopt AI-L 6	0.953				
Perceived usefulness of AI Lecturer	PU AI-L 1	0.935	0.963	0.963	0.971	0.870
	PU AI-L 2	0.94				
	PU AI-L 3	0.941				
	PU AI-L 4	0.914				
	PU AI-L 5	0.933				
Student's attitudes towards AI Lecturer	ST AI 1	0.673	0.976	0.977	0.977	0.625
	ST AI 10	0.793				
	ST AI 11	0.790				
	ST AI 12	0.811				
	ST AI 13	0.731				
	ST AI 14	0.790				
	ST AI 15	0.815				
	ST AI 16	0.814				
	ST AI 17	0.810				
	ST AI 18	0.831				
	ST AI 19	0.849				
	ST AI 2	0.715				
	ST AI 20	0.843				
	ST AI 21	0.838				
	ST AI 22	0.796				
	ST AI 23	0.862				
	ST AI 24	0.824				
	ST AI 25	0.862				
	ST AI 26	0.776				
	ST AI 3	0.705				
	ST AI 4	0.708				
	ST AI 5	0.769				
	ST AI 6	0.739				
	ST AI 7	0.775				
	ST AI 8	0.760				
	ST AI 9	0.830				

Figure 2 Measurement Model Evaluation



According to Low and Memon (2022), it is advised to use the heterotrait-monotrait (HTMT) criterion while conducting discriminant validity testing. This meets the requirements of the HTMT ratio of correlation criterion for assessing discriminant validity. The determination of discriminant validity occurs when the HTMT statistics are less than or equal to 0.85 or 0.90. Table 3 demonstrates that there are no HTMT values greater than 0.90. Additionally, number of the Table 3 confidence interval values do not show a value of 1 in between, suggesting that discriminant validity has been established.

Table 3 HTMT Discriminant Validity criteria

	Attitude on AI	**Attitude towards AI-L**	**EOC AI-L**	**Int adopt AI-L**	**PU AI-L**
Attitude on AI					
Attitude towards AI-L	0.782				
EOC AI-L	0.811	0.835			
Int adopt AI-L	0.764	0.828	0.774		
PU AI-L	0.775	0.842	0.862	0.830	

4.3 Structural Model Evaluation

According of Tamura et al. (2019), variance inflation factor (VIF) needs to be less than the given upper limit. The optimal solution becomes trivial and nonsensical if VIF is minimised as the objective function; that is, a subset with just one explanatory variable. As a result, VIF should not be regarded as the objective function; instead, it should be constrained by the upper bound. A greater R-squared (R^2) value is preferable. The coefficient of determination, or R^2, measures the variances explained by the exogenous variable. Consequently, it is preferable to use an approach that yields a higher R^2 value. According to Hair et al. (2019), higher values of the R^2, which has a range of 0 to 1, indicate a higher explanatory power. R^2 values of 0.75, 0.50, and 0.25 are generally regarded as significant, moderate, and weak. As demonstrated in Table 5, the VIF which is used to evaluate the collinearity problem, has a value less than 5, meaning that multicollinearity is not a problem. R^2 value in Table 5 shows all numbers are around 0.5 to 0.7, which implies the variables explain moderately.

Table 4 The results of the Structural Model Evaluation

	VIF	**f2**		**R-square**	**R-square adjusted**
Attitude on AI -> EOC AI-L	1.000	1.476	**Attitude towards AI-L**	0.701	0.698
Attitude on AI -> PU AI-L	1.000	1.312	**EOC AI-L**	0.596	0.594
Attitude towards AI-L -> Int adopt AI-L	1.000	1.744	**Int adopt AI-L**	0.636	0.634
EOC AI-L -> Attitude towards AI-L	2.979	0.162	**PU AI-L**	0.568	0.566
PU AI-L -> Attitude towards AI-L	2.979	0.278			

4.4 Hypotheses Testing

The basic study framework's H1 to H7 assumptions were tested using the sample of 252 respondents. Any hypothesis for which the corresponding route coefficient was greater than 0.1 and significant at $p < 0.05$ was confirmed by Lohmöeller (1989). H1 is significant, according to Table 5's data, with an original sample of 0.753, $p = 0.00$, and a t statistic greater than 1.96. H2 with an original sample of 0.772, p value of 0.000, and t statistics of 20.887, even higher than 1.96. H3 to H7 are also significant in a similar manner. However, H6 original sample of 0.092, $p = 0.169$, and a t statistic of 0.96 lower than 1.96. It is not supported the positive relationship of ease of communication on intention to adopt AI Lecturer. Figure 2 displays the bootstrapping results of the hypothesis testing.

Table 5 Structural Model

	Original sample (O)	**Sample mean (M)**	**Standard deviation (STDEV)**	**T statistics (|O/STDEV|)**	**P values**	**Supported**
H1: Attitude on AI -> PU AI-L	0.753	0.756	0.037	20.18	0.000	Supported
H2: Attitude on AI -> EOC AI-L	0.772	0.773	0.037	20.89	0.000	Supported
H3: PU AI-L -> Attitude towards AI-L	0.497	0.499	0.096	5.196	0.000	Supported
H4: EOC AI-L -> Attitude towards AI-L	0.381	0.38	0.09	4.217	0.000	Supported
H5: PU AI-L -> Int adopt AI-L	0.407	0.402	0.114	3.562	0.000	Supported
H6: EOC AI-L -> Int adopt AI-L	0.092	0.094	0.096	0.960	0.169	Not Supported
H7: Attitude towards AI-L -> Int adopt AI-L	0.396	0.399	0.112	3.519	0.000	Supported

4.5 Conclusion

Chapter 4 provides an overview of the data analysis and interpretation of the study's data. The discussion, conclusion, and implications will be presented and discussed in the ensuing Chapter 5.

CHAPTER 5: DISCUSSION, CONCLUSION, AND IMPLICATIONS

5. Discussion, Conclusion, and Implications

This chapter discusses the findings from the preceding chapter. This chapter contains the main conclusions, implications, management implications, and study limitations. This chapter will conclude with some recommendations for the future and further study.

5.1 Research Design Discussion of Major Findings

This study uses FATE theory and TAM theory to explore and research the students' perspectives on non-human lecturers. The independent variables of student's attitude toward Artificial Intelligence (AI), perceived usefulness of an AI Lecturer, ease of communication with AI Lecturer, attitude toward using AI Lecturer; and the dependent variable of intention to adopt AI Lecturer. AI has emerged as a transformative force in tertiary education, specifically through the introduction of non-human lecturers. Students' perspectives on this innovation reveal a nuanced landscape of benefits and concerns.

According to Baidoo and Ansah (2023), one of the primary advantages highlighted by students is the unparalleled accessibility and flexibility offered by AI-powered lecturers. These digital educators allow students to engage with course materials at their own pace and convenience, accommodating diverse schedules and learning preferences. The ability to personalize learning experiences is another lauded aspect of AI in education.

Ethical considerations surrounding data privacy and biases in AI algorithms also surface as critical concerns. Students are wary of how their personal data is collected and utilized by these systems, urging for transparency and safeguards to protect their privacy. Additionally, technical challenges and the learning curve associated with adopting AI-based platforms pose initial hurdles for some students, necessitating support and guidance (Mouawad, 2020).

Students perceive AI as a valuable addition to tertiary education, offering unparalleled flexibility, personalization, and engagement. Nevertheless, they advocate for a balanced approach where AI complements human educators rather than replaces them. The ideal scenario, as envisioned by students, is a collaborative partnership between AI and human lecturers, leveraging the strengths of both to create a more holistic and effective educational experience (Holstein, 2019).

5.1.1 Finding on Hypothesis

There are seven hypotheses developed in testing the interrelationship of the variables which are H1 to H7. Table 5 and Figure 3 in Chapter 4 show the results of the relationships. The following deliberations of the hypotheses results are made in reference to Chapter4, particularly Table 5.

H1: Student's attitudes towards AI have a positive relationship on perceived usefulness of AI Lecturer.

Result: P=0.000 ($p < 0.05$), Decision: supported

Table 5 shows H1 that a positive relationship between student's attitudes towards AI and perceived usefulness of AI Lecturer is supported by the research. According to Ayanwale (2022), this positive relationship stems from the alignment between students' optimistic perceptions of AI's capabilities and their acknowledgement of how an AI lecturer can enhance their learning experiences. When students view AI favourably, they tend to appreciate the lecturer's contributions, seeing it as a valuable tool that aids comprehension, engagement, and accessibility in education, thereby reinforcing the perceived usefulness of AI in the role of a lecturer.

H2: Student's attitudes towards AI have a positive relationship on perceived ease of communication of AI Lecturer.

Result: P=0.000 ($p < 0.05$), Decision: supported

Table 5 shows H2 that a positive relationship between student's attitudes towards AI and ease of communication with AI Lecturer is supported by the research. When students hold favourable views of AI, they tend to find it easier to interact with AI-driven instructors. This ease of communication stems from increased comfort, openness to technology, positive expectations, trust in AI, and quicker adaptation to the AI lecturer's communication style and functionalities (Chen et al., 2021). Educators and developers benefit from acknowledging and addressing these attitudes, as they significantly influence the acceptance and effectiveness of AI-based educational tools in academic settings.

H3: Perceived usefulness has a positive relationship on attitude towards AI Lecturer.

Result: P=0.000 ($p < 0.05$), Decision: supported

Table 5 shows H3 that a positive relationship between perceived usefulness and attitude towards AI Lecturer is supported by the research. According to Kim et al. (2020), when student perceives AI as helpful and valuable in the role of a lecturer, it significantly influences their attitude toward AI in education. This positive relationship suggests that when student believe AI enhances teaching effectiveness, facilitates learning, or simplifies tasks for educators, it fosters a favourable attitude toward AI in the academic sphere. This positive perception often leads to a more open-minded and accepting approach toward integrating AI technology in educational settings.

H4: Ease of communication has a positive relationship on attitudes towards AI Lecturer.

Result: P=0.000 ($p < 0.05$), Decision: supported

Table 5 shows H4 that a positive relationship between ease of communication and attitude towards AI Lecturer is supported by the research. When communication with AI is smooth, clear, and intuitive, individuals tend to develop more positive attitudes. Clear communication enhances student understanding, fosters trust, and reduces any perceived barriers between student and AI (Wang et al., 2021). When student feel comfortable and confident interacting with AI lecturers, it promotes a sense of ease, leading to increased acceptance, and receptiveness towards the technology and its educational applications.

H5: Perceived usefulness has a positive relationship on intention to adopt AI Lecturer.

Result: P=0.000 ($p < 0.05$), Decision: supported

Table 5 shows H5 that a positive relationship between perceived usefulness and intention to adopt AI Lecturer is supported by the research. Perceived usefulness refers to how valuable someone believes a technology or tool, like AI in this case, is in assisting them with their tasks or goals. When individuals perceive AI as useful for their work as a student—maybe in research or enhancing learning methods—they are more likely to intend to adopt it (Kim et al., 2020). This positive relationship means that the more they see AI as beneficial or advantageous, the stronger their inclination to incorporate it into their study practices.

H6: Ease of communication has a positive relationship on intention to adopt AI Lecturer.

Result: P=0.169 ($p < 0.05$), Decision: not supported

Table 5 shows H6 that a positive relationship between ease of communication and intention to adopt AI Lecturer is not supported by the research. According to Alkhateeb

et al. (2023), the negative relationship between ease of communication and intention to adopt AI by lecturers implies that when communication becomes overly simplified or effortless due to AI's intervention, there might be a decrease in the willingness of lecturers to embrace it. When the ease of communication through AI surpasses a certain threshold, it may inadvertently lower the motivation or interest of lecturers in adopting such technology, as it might be perceived as a challenge to their roles or diminish the significance of their expertise in fostering direct connections with students.

H7: Attitudes towards AI Lecturer has a positive relationship on intention to adopt AI Lecturer.

Result: P=0.000 ($p < 0.05$), Decision: supported

Table 5 shows H7 that a positive relationship between attitudes towards AI Lecturer and intention to adopt AI Lecturer is supported by the research. According to Wang et al. (2021), when students perceive AI lecturers as effective, engaging, and supportive of their learning needs, they tend to develop a favourable attitude. Factors such as personalized interactions, adaptive teaching methods, and the ability of AI lecturers to cater to individual learning styles contribute to this positive relationship. When students believe that AI lecturers enhance their learning experiences and supplement traditional teaching, they are more inclined to adopt and embrace AI in education, fostering an intention to engage with AI lecturers as an integral part of their learning journey.

5.2 Implications of the Study

5.2.1 The practical implications for policymakers and practitioners:

According to Miao et al. (2021), the insights gleaned from students' perspectives on AI-driven lecturers have tangible implications for policy formation and educational practitioners. Firstly, these perspectives guide resource allocation strategies. Policymakers can use this understanding to allocate budgets effectively for AI-driven educational technology, catering to student needs and preferences.

Moreover, curriculum development stands to benefit from these insights. By understanding how students engage with AI lecturers, policymakers can shape educational programs that effectively integrate AI-based teaching methods. This integration aligns with students' learning preferences and ensures a more engaging learning environment (Miao et al., 2021).

Additionally, the study's findings influence training and support mechanisms. Educational institutions can design targeted training programs for faculty and staff, enabling them to adeptly integrate AI tools into their teaching methodologies. Addressing concerns highlighted by student perspectives becomes pivotal in developing ethical guidelines for AI use in education (George & Wooden, 2023).

5.2.2 The practical implications for practitioners:

For educators, understanding students' perceptions of non-human lecturers guides the adaptation of teaching methods. Incorporating AI tools aligned with student preferences enhances the efficacy of educational delivery. Furthermore, personalized learning experiences can be crafted, catering to individual student needs, and enhancing learning outcomes (Pedro et al., 2019). The integration of AI also revolutionizes feedback and

assessment. With AI's assistance, educators can provide prompt and personalized feedback, allowing them to focus more on tailored guidance and mentorship.

5.2.3 The theoretical implications from an academic perspective:

From an academic viewpoint, this exploration contributes significantly to pedagogical theory. According to Mohd et al. (2020), understanding how AI impacts student engagement, learning outcomes, and the student-teacher relationship enriches existing pedagogical discourse. Delving into the sociotechnical implications of AI in education becomes imperative. This involves examining the social, cultural, and ethical dimensions of integrating AI into the learning environment. Ethical considerations, such as data privacy, algorithmic bias, and the implications for human agency in the learning process, become essential focal points for academic exploration.

5.3 Limitation of the Study

According to Schiff (2021), the limitation revolves around the potential lack of nuanced understanding and empathy that AI might have compared to human instructors. Students might find it challenging to relate to non-human lecturers on a personal level or seek the emotional support and guidance they often seek from human educators.

Another limitation is the current limitations in AI's ability to adapt to diverse learning styles and respond dynamically to individual student needs (Kabudi, 2021). AI might struggle to provide the same level of personalized assistance and tailored feedback that human instructors can offer based on their experience and intuition.

Moreover, concerns regarding the 'black box' nature of AI algorithms might arise, leading to questions about transparency and bias within the educational content or assessment systems

developed by AI (von Eschenbach, 2021). Students may question the fairness and objectivity of AI-driven evaluations or content delivery methods.

Despite these limitations, it is important to note that they do not diminish the significance of exploring AI's role in education. Instead, they serve as crucial areas for future research and improvement. Acknowledging these limitations provides a platform for further investigation and refinement of AI systems in education to ensure they complement and enhance the learning experience without replacing the valuable aspects of human interaction and understanding.

5.4 Recommendation

The pivotal recommendations when considering AI integration in tertiary education involves prioritizing user-centric design. Engaging students in the developmental stages of AI-driven educational tools is essential. Soliciting feedback and incorporating their preferences and concerns ensures that these technologies align with their learning needs and expectations. This participatory approach fosters a sense of ownership and relevance, enhancing the efficacy of AI applications.

According to Nguyen et al. (2023), transparency and explanation within AI systems play a crucial role in garnering student trust. As AI generates educational content or conducts assessments, providing clear explanations of the decision-making process behind these activities is imperative. Understanding how AI creates content, conducts assessments, and generates feedback builds confidence among students, fostering a deeper engagement with the AI-driven learning platforms.

Personalization and adaptability stand as cornerstones for effective AI integration. Tailoring learning experiences to accommodate diverse learning styles and individual preferences is paramount. Developing AI systems capable of adaptive learning, offering customized content and feedback, enhances the relevance and effectiveness of education delivery, catering to the unique needs of each student (Murtaza et al, 2022).

Moreover, emphasizing the complementary nature of AI and human educators is crucial. Collaboration between AI systems and human instructors can leverage the strengths of both (Holstein, 2019). While AI might excel in data processing and content delivery, human educators bring empathetic understanding and nuanced interaction. This collaboration creates a balanced and enriched learning environment that combines technological prowess with human intuition and experience.

Furthermore, adequate education and familiarization with AI-driven tools are crucial. Providing training to both students and educators on utilizing these technologies effectively fosters a culture of familiarity and comfort. Empowering individuals with the knowledge to leverage AI maximizes its benefits in education.

5.5 Conclusion

In exploring AI's role in tertiary education, especially concerning non-human lecturers from students' perspectives, it's clear that AI offers promise but also challenges. Prioritizing students' needs, ensuring transparency, personalization, collaboration, and ethical considerations are vital. While limitations exist, these should be seen as opportunities for further research and refinement. By valuing both AI and human educators' strengths and continuously addressing student concerns, we pave the way for a more enriched, inclusive learning environment where technology and human insight work hand in hand to elevate education.

REFERENCES

Abdullah, F., & Ward, R. (2016). Developing a General Extended Technology Acceptance Model for E-Learning (GETAMEL) by analysing commonly used external factors. Computers in human behavior, 56, 238-256.

Abdullah, F., Ward, R., & Ahmed, E. (2016). Investigating the influence of the most commonly used external variables of TAM on students' Perceived Ease of Use (PEOU) and Perceived Usefulness (PU) of e-portfolios. Computers in human behavior, 63, 75-90.

Ahmed, S., Khalil, M. I., Chowdhury, B., Haque, R., bin S Senathirajah, A. R., & bin Omar Din, F. M. (2022). Motivators and barriers of artificial intelligent (AI) based teaching. Eurasian Journal of Educational Research, 100(100), 74-89.

Al-Adwan, A. S., Li, N., Al-Adwan, A., Abbasi, G. A., Albelbisi, N. A., & Habibi, A. (2023). Extending the Technology Acceptance Model (TAM) to Predict University Students' Intentions to Use Metaverse-Based Learning Platforms. Education and Information Technologies, 1-33.

Al-Hattami, H. M. (2023). Understanding perceptions of academics toward technology acceptance in accounting education. Heliyon, 9(1).

Alkhateeb, M., Duné, E., & Akriem, E. (2023). The Impact of AI On Internal Communication Within An Organization: A Critical Examination of AI Adoption.

Allen, I. E., & Seaman, J. (2017). Digital Compass Learning: Distance Education Enrollment Report 2017. Babson survey research group.

Alloghani, M., Hussain, A., Al-Jumeily, D., & Abuelma'atti, O. (2015, December). Technology Acceptance Model for the Use of M-Health Services among health related users in UAE. In 2015 International Conference on Developments of E-Systems Engineering (DeSE) (pp. 213-217). IEEE.

Altmiller, G., & Pepe, L. H. (2022). Influence of technology in supporting quality and safety in nursing education. Nursing Clinics, 57(4), 551-562.

Ayanwale, M. A., Sanusi, I. T., Adelana, O. P., Aruleba, K. D., & Oyelere, S. S. (2022). Teachers' readiness and intention to teach artificial intelligence in schools. *Computers and Education: Artificial Intelligence*, *3*, 100099.

Baidoo-Anu, D., & Ansah, L. O. (2023). Education in the era of generative artificial intelligence (AI): Understanding the potential benefits of ChatGPT in promoting teaching and learning. *Journal of AI*, *7*(1), 52-62.

Black, K. (2023). Business statistics: for contemporary decision making. John Wiley & Sons.

Chen, L., Chen, P., & Lin, Z. (2020). Artificial intelligence in education: A review. Ieee Access, 8, 75264-75278.

Chen, J. S., Le, T. T. Y., & Florence, D. (2021). Usability and responsiveness of artificial intelligence chatbot on online customer experience in e-retailing. *International Journal of Retail & Distribution Management*, *49*(11), 1512-1531.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS quarterly, 319-340.

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.

Eagly, A. H., & Chaiken, S. (1993). The psychology of attitudes. Harcourt brace Jovanovich college publishers.

Edwards, C., Edwards, A., Albrehi, F., & Spence, P. (2021). Interpersonal impressions of a social robot versus human in the context of performance evaluations. Communication Education, 70(2), 165-182.

ElKheshin, S. A., & Saleeb, N. (2020). Assessing the adoption of e-government using TAM model: case of Egypt. International Journal of Managing Information Technology (IJMIT), 12(1), 1-14.

Fahimirad, M., & Kotamjani, S. S. (2018). A review on application of artificial intelligence in teaching and learning in educational contexts. International Journal of Learning and Development, 8(4), 106-118.

George, B., & Wooden, O. (2023). Managing the strategic transformation of higher education through artificial intelligence. *Administrative Sciences*, *13*(9), 196.

Gunawardena, C. N., & Zittle, F. J. (1997). Social presence as a predictor of satisfaction within a computer-mediated conferencing environment. American journal of distance education, 11(3), 8-26.

Hair Jr, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., Danks, N. P., & Ray, S. (2021). Partial least squares structural equation modeling (PLS-SEM) using R: A workbook (p. 197). Springer Nature.

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European business review, 31*(1), 2-24.

Hair, J. F., Sarstedt, M., & Ringle, C. M. (2019). Rethinking some of the rethinking of partial least squares. European Journal of Marketing, 53(4), 566–584.

Haleem, A., Javaid, M., Qadri, M. A., & Suman, R. (2022). Understanding the role of digital technologies in education: A review. Sustainable Operations and Computers, 3, 275-285.

Halili, S. H. (2019). Technological advancements in education 4.0. The Online Journal of Distance Education and e-Learning, 7(1), 63-69.

Heath, J., Williamson, H., Williams, L., & Harcourt, D. (2018). "It's just more personal": Using multiple methods of qualitative data collection to facilitate participation in research focusing on sensitive subjects. Applied Nursing Research, 43, 30-35.

Holstein, K. (2019). Designing real-time teacher augmentation to combine strengths of human and AI instruction. *Unpublished doctoral dissertation, Carnegie Mellon University*.

Hu, K. H. (2023). An exploration of the key determinants for the application of AI-enabled higher education based on a hybrid Soft-computing technique and a DEMATEL approach. Expert Systems with Applications, 212, 118762.

Kabudi, T., Pappas, I., & Olsen, D. H. (2021). AI-enabled adaptive learning systems: A systematic mapping of the literature. *Computers and Education: Artificial Intelligence, 2*, 100017.

Kaliyadan, F., & Kulkarni, V. (2019). Types of variables, descriptive statistics, and sample size. Indian dermatology online journal, 10(1), 82.

Kandel, B. (2020). Qualitative Versus Quantitative Research. Journal of Product Innovation Management, 32(5), 658.

Kaur, P., Stoltzfus, J., & Yellapu, V. (2018). Descriptive statistics. International Journal of Academic Medicine, 4(1), 60.

Kim, J., Merrill Jr, K., Xu, K., & Sellnow, D. D. (2021). I like my relational machine teacher: An AI instructor's communication styles and social presence in online education. International Journal of Human–Computer Interaction, 37(18), 1760-1770.

Kim, J., Merrill, K., Kun, X., & Sellnow, D. D. (2022). Embracing AI-based education: Perceived social presence of human teachers and expectations about machine teachers in online education. Human-Machine Communication, 4, 169-184.

Kim, J., Merrill, K., Xu, K., & 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, 36(20), 1902-1911.

Kurent, B., & Avsec, S. (2023). Examining pre-service teachers regulation in distance and traditional preschool design and technology education. Heliyon, 9(2).

Lamm, A. J., & Lamm, K. W. (2019). Using non-probability sampling methods in agricultural and extension education research. Journal of International Agricultural and Extension Education, 26(1), 52-59.

Lohmöller, J. B., & Lohmöller, J. B. (1989). Predictive vs. structural modeling: Pls vs. ml. *Latent variable path modeling with partial least squares*, 199-226.

Low, M. P., & Memon, M. A. The interrelations between micro-level CSR, Job engagement and organizational engagement during the COVID-19 pandemic: A PLSpredict model assessment. Human Systems Management, (Preprint), 1-22.

Luckin, R., & Holmes, W. (2016). Intelligence unleashed: An argument for AI in education.

Memon, M. A., Ramayah, T., Cheah, J. H., Ting, H., Chuah, F., & Cham, T. H. (2021). PLS SEM statistical programs: a review. *Journal of Applied Structural Equation Modeling*, *5*(1), 1-14.

Miao, F., Holmes, W., Huang, R., & Zhang, H. (2021). *AI and education: A guidance for policymakers*. UNESCO Publishing.

Mkandawire, S. B. (2019). Selected common methods and tools for data collection in research. Marvel Publishers.

Mouawad, G. P. (2020). Students' Privacy in a Digital Age (Doctoral dissertation, University of La Verne).

Mohd, I. H., Tuan Besar, T. B. H., & Sharkawi, S. (2020). Enriching Students' Learning Experience and Classroom Enrichment using Online Classroom Games. *Malaysian Journal of Qualitative Research*, *6*(1).

Muchran, M., & Ahmar, A. S. (2019). Application of TAM model to the use of information technology. arXiv preprint arXiv:1901.11358.

Murtaza, M., Ahmed, Y., Shamsi, J. A., Sherwani, F., & Usman, M. (2022). AI-based personalized e-learning systems: Issues, challenges, and solutions. *IEEE Access*.

Mwita, K. (2022). Factors to consider when choosing data collection methods. International Journal of Research in Business and Social Science (2147-4478), 11(5), 532-538.

Nguyen, T. T. T. (2023). Citizens' intentions to use e-government during the COVID-19 pandemic: integrating the technology acceptance model and perceived risk theory. Kybernetes.

Nguyen, A., Ngo, H. N., Hong, Y., Dang, B., & Nguyen, B. P. T. (2023). Ethical principles for artificial intelligence in education. *Education and Information Technologies*, *28*(4), 4221-4241.

Patel M, Patel N. Exploring research methodology: review article. International Journal of Research and Review. 2019; 6(3):48-55.

Pedro, F., Subosa, M., Rivas, A., & Valverde, P. (2019). Artificial intelligence in education: Challenges and opportunities for sustainable development.

Rogers, G., Szomszor, M. & Adams, J. Sample size in bibliometric analysis. Scientometrics 125, 777–794 (2020). https://doi.org/10.1007/s11192-020-03647-7

Roy, R., Babakerkhell, M. D., Mukherjee, S., Pal, D., & Funilkul, S. (2022). Evaluating the intention for the adoption of artificial intelligence-based robots in the university to educate the students. IEEE Access, 10, 125666-125678.

Sánchez-Prieto, J. C., Cruz-Benito, J., Therón, R., & García-Peñalvo, F. J. (2019, October). How to measure teachers' acceptance of AI-driven assessment in eLearning: A TAM-based proposal. In Proceedings of the Seventh International Conference on Technological Ecosystems for Enhancing Multiculturality (pp. 181-186).

Schepman, A., & Rodway, P. (2020). Initial validation of the general attitudes towards Artificial Intelligence Scale. Computers in human behavior reports, 1, 100014.

Schiff, D. (2021). Out of the laboratory and into the classroom: the future of artificial intelligence in education. *AI & society*, *36*(1), 331-348.

Sekaran, U. (2003). Determining sample size. Sekaran. Uma (4th Eds.), Research methods for business: A skill building approach, 263-298.

Sharma, G. (2017). Pros and cons of different sampling techniques. International journal of applied research, 3(7), 749-752.

Sheard, L. (2022). Telling a story or reporting the facts? Interpretation and description in the qualitative analysis of applied health research data: a documentary analysis of peer review reports. SSM-Qualitative Research in Health, 2, 100166.

Suh, W., & Ahn, S. (2022). Development and validation of a scale measuring student attitudes toward artificial intelligence. Sage Open, 12(2), 21582440221100463.

Sun, Z., Anbarasan, M., & Praveen Kumar, D. J. C. I. (2021). Design of online intelligent English teaching platform based on artificial intelligence techniques. Computational Intelligence, 37(3), 1166-1180.

Swedberg, R. (2020). Exploratory research. The production of knowledge: Enhancing progress in social science, 17-41.

Tamura, R., Kobayashi, K., Takano, Y., Miyashiro, R., Nakata, K., & Matsui, T. (2019). Mixed integer quadratic optimization formulations for eliminating multicollinearity based on variance inflation factor. *Journal of Global Optimization*, *73*, 431-446.

Tang, J. (2023). Research Scale of College Students' Attitude towards Learning under the Influence of Artificial Intelligence. Advances in Educational Technology and Psychology, 7(4), 1-6.

Tekkol, İ. A., & Demirel, M. (2018). An investigation of self-directed learning skills of undergraduate students. Frontiers in psychology, 9, 2324.

Tekkol, I. A., & Demirel, M. (2022). An Investigation of Preschool Teacher Candidates' Lifelong Learning Tendencies. International Journal of Progressive Education, 18(5), 133-145.

Urdan, T. C. (2022). Statistics in plain English. Taylor & Francis.

von Eschenbach, W. J. (2021). Transparency and the black box problem: Why we do not trust AI. *Philosophy & Technology*, *34*(4), 1607-1622.

Wang, Q., Saha, K., Gregori, E., Joyner, D., & Goel, A. (2021, May). Towards mutual theory of mind in human-ai interaction: How language reflects what students perceive about a virtual teaching assistant. In *Proceedings of the 2021 CHI conference on human factors in computing systems* (pp. 1-14).

Wang, S., Wang, H., Jiang, Y., Li, P., & Yang, W. (2021). Understanding students' participation of intelligent teaching: an empirical study considering artificial intelligence usefulness, interactive reward, satisfaction, university support and enjoyment. Interactive Learning Environments, 1-17.

Wang, Y., Liu, C., & Tu, Y. F. (2021). Factors affecting the adoption of AI-based applications in higher education. Educational Technology & Society, 24(3), 116-129.

Ye, J. H., Lee, Y. S., Wang, C. L., Nong, W., Ye, J. N., & Sun, Y. (2023). The continuous use intention for the online learning of Chinese vocational students in the post-epidemic era: the extended technology acceptance model and expectation confirmation theory. Sustainability, 15(3), 1819.

Zhai, X., Chu, X., Chai, C. S., Jong, M. S. Y., Istenic, A., Spector, M., ... & Li, Y. (2021). A Review of Artificial Intelligence (AI) in Education from 2010 to 2020. Complexity, 2021, 1-18.

Appendices A: Survey Questionnaire

UNIVERSITI TUNKU ABDUL RAHMAN (UTAR)

FACULTY OF ACCOUNTANCY AND MANAGEMENT (FAM)

Bachelor of International Business (Hons)

Exploring the Role of Artificial Intelligence (AI) in Tertiary Education: Students' Perspectives on Non-Human Lectures

Survey Questionnaire

Dear Esteemed Respondents

I am a student of the Faculty of Accountancy and Management from Universiti Tunku Abdul Rahman (UTAR). This research project is to explore the Role of Artificial Intelligence (AI) in Tertiary Education: Students' Perspectives on Non-Human Lecturers between student's attitudes toward AI.

I humbly request your voluntary participation in this study. It's important that you have an understanding of the purposes and processes of the study before deciding if you're going to take part. Please take your time reading the following information. If there is anything confusing or if you require more information, do ask the researcher.

The study aims to examine the students' perception of AI teaching with variables covering student's attitudes toward AI, perceived usefulness of an AI lecturer, ease of communication with an AI lecturer, attitude toward using AI lecturer, and intention to adopt AI lecturer. This study consists of 3 sections. For the first section, I will present a consent form to inform you about our study and what questions will be covered in the upcoming session. As for the second section, respondents' demographic data will be collected. For the third section, questions

regarding our variables, which are between students' attitudes toward AI, perceived usefulness of an AI lecturer, ease of communication with an AI lecturer, attitude toward using an AI lecturer, and intention to adopt an AI lecturer will be asked. The estimation of time to complete this survey is 10 minutes.

There is no potential risk in answering the questionnaire. Your confidentiality is assured. The data collected is meant for academic purpose and the information will be aggregated.

Contact the undersigned researcher if you have any questions about this study at any time or if taking part in it has caused you to experience any adverse effects. If you have any concerns about your rights as a research participant or run into issues that you do not feel comfortable discussing, contact the researcher at 018-940-5689 or email at lohyiwen1213@1utar.my (Loh Yi Wen).

Yours sincerely,

Loh Yi Wen 20UKB05789

Section A Demographic

1. Gender
   - ☐ Male
   - ☐ Female

2. Education Level
   - ☐ Degree
   - ☐ Postgraduate (e.g.Master and above)

3. Year Semester
   - ☐ Year 1
   - ☐ Year 2
   - ☐ Year 3
   - ☐ Year 4

4. Type of University:
   Public University
   Private University

5. Faculty
   - ☐ Medical (eg. Medical studies, Bachelor of Rehabilitation, Physiotherapist)
   - ☐ Pure Science (eg. Engineering, Biotechnology)
   - ☐ Social Science (eg. Accountancy, Management, Business, Finance)
   - ☐ Others. Please specify _____

6. Race
   - ☐ Malay
   - ☐ Indian
   - ☐ Chinese
   - ☐ Others. Please specify _____

7. Result (CGPA):
   - ☐ Below 2.0
   - ☐ 2.0-3.0
   - ☐ Above 3.0

8. Have you ever taken a class taught by a non-human lecturer?
   Example: Sign up online class to learn Korean.
   - ☐ Yes
   - ☐ No

Section B: Survey Questionnaire

Please choose how much you agree or disagree with each of the following statements based on a scale ranging from 1(strongly disagree) to 7(strongly agree).

1- Strongly Disagree (SD)	2- Disagree (D)	3- Somewhat Disagree (SWD)	4- Neutral (N)	5- Somewhat Agree (SWA)	6- Agree (A)	7- Strongly Agree (SA)

Ia	**Student's Attitudes toward AI (Cognitive components)**	**SD**	**D**	**SWD**	**N**	**SWA**	**A**	**SA**
1	I think that teaching students about AI in the classroom is important.	1	2	3	4	5	6	7
2	AI class is important.	1	2	3	4	5	6	7
3	I think AI courses need to be taught in schools.	1	2	3	4	5	6	7
4	In my opinion, all students should study AI in school.	1	2	3	4	5	6	7
Ib	**Student's Attitudes toward AI (Affective components)**	**SD**	**D**	**SWD**	**N**	**SWA**	**A**	**SA**
5	AI is necessary for the development of society.	1	2	3	4	5	6	7
6	In my opinion, AI makes life easier for people.	1	2	3	4	5	6	7
7	AI has a connection to my life.	1	2	3	4	5	6	7
8	I will use AI to find solutions for problems that I face every day.	1	2	3	4	5	6	7
9	AI helps me in real-world problem-solving.	1	2	3	4	5	6	7

10	In the future, AI will be essential to my life.	1	2	3	4	5	6	7
11	Everyone needs AI.	1	2	3	4	5	6	7
12	AI produces more benefits than drawbacks.	1	2	3	4	5	6	7
13	AI needs further investigation.	1	2	3	4	5	6	7
14	In my opinion, most careers in the future will require knowledge of AI.	1	2	3	4	5	6	7
Ic	**Student's Attitudes toward AI (Behavioural components)**	**SD**	**D**	**SWD**	**N**	**SWA**	**A**	**SA**
15	The field of AI is the place I want to work.	1	2	3	4	5	6	7
16	I will choose a position in the AI industry.	1	2	3	4	5	6	7
17	If there were a club about AI, I would join it.	1	2	3	4	5	6	7
18	I enjoy employing AI-related objects.	1	2	3	4	5	6	7
19	Learning about AI is enjoyable.	1	2	3	4	5	6	7
20	I wish to keep learning more about AI.	1	2	3	4	5	6	7
21	I am interested in watching videos online on AI.	1	2	3	4	5	6	7
22	Using AI, I want to create something that makes life easier for people.	1	2	3	4	5	6	7
23	The development of AI interests me.	1	2	3	4	5	6	7
24	The use of AI is interesting.	1	2	3	4	5	6	7
25	There should be more time spent discussing AI in class.	1	2	3	4	5	6	7
26	I am knowledgeable about AI.	1	2	3	4	5	6	7
II	**Perceived usefulness of an AI Lecturer**	**SD**	**D**	**SWD**	**N**	**SWA**	**A**	**SA**
1	My learning experience would improve if I used an AI lecturer.	1	2	3	4	5	6	7
2	My ability to study more effectively would increase if I used an AI lecturer.	1	2	3	4	5	6	7

3	My studies would be easier if I have an AI lecturer.	1	2	3	4	5	6	7
4	I could use an AI lecturer to coach me in my coursework.	1	2	3	4	5	6	7
5	I could complete tasks faster in my study if I have an AI lecturer.	1	2	3	4	5	6	7
III	**Ease of communication with AI Lecturer**	**SD**	**D**	**SWD**	**N**	**SWA**	**A**	**SA**
1	With an AI lecturer, learning how to communicate with it would be simple.	1	2	3	4	5	6	7
2	An AI lecturer wouldn't require much of my mental effort to interact with.	1	2	3	4	5	6	7
3	My communication with the AI lecturer would be simple and clear.	1	2	3	4	5	6	7
4	I think interacting with an AI lecturer would be flexible.	1	2	3	4	5	6	7
IV	**Attitude toward using AI Lecturer**	**SD**	**D**	**SWD**	**N**	**SWA**	**A**	**SA**
1	Utilizing an AI lecturer increases the standard of my study.	1	2	3	4	5	6	7
2	I have more control over my study when I have an AI lecturer.	1	2	3	4	5	6	7
3	I can learn more effectively when I have an AI lecturer.	1	2	3	4	5	6	7
4	I believe that with some adjustments, the AI lecturer could be even more user-friendly for me.	1	2	3	4	5	6	7
5	Having an AI lecture can learn more technical skills.	1	2	3	4	5	6	7
V	**Intention to adopt AI Lecturer**	**SD**	**D**	**SWD**	**N**	**SWA**	**A**	**SA**
1	If there was an online course with an AI lecturer, I would consider taking it.	1	2	3	4	5	6	7
2	I would be interested in participating in an online course that uses an AI Lecturer.	1	2	3	4	5	6	7

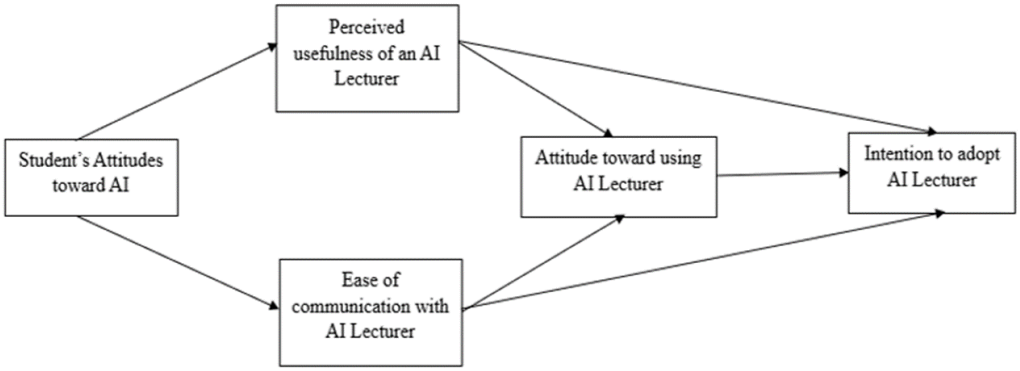
3	I intent to register for courses with AI lecturer.	1	2	3	4	5	6	7
4	I would like to have AI lecturer as my lecturer.	1	2	3	4	5	6	7
5	I would recommend to my friends to have AI lecturer.	1	2	3	4	5	6	7
6	It is likely that I will register in courses that with AI lecturer.	1	2	3	4	5	6	7

THE END

THANK YOU FOR YOUR PARTICIPATION

Appendices B: Tables and Figures

Appendices 2.1: Framework



Source: Developed for the research.

Appendices 3.1: Measurement Instrument and Measurement Scale

Construct	Measurement Items	Scale	Source
Student's Attitudes toward AI *(Cognitive components)*	27. I think that teaching students about AI in the classroom is important. 28. AI class is important. 29. I think AI courses need to be taught in schools. 30. In my opinion, all students should study AI in school.	1 = Strongly Disagree, 7 = Strongly Agree	Suh and Ahn (2022)
Student's Attitudes toward AI *(Affective components)*	31. AI is necessary for the development of society. 32. In my opinion, AI makes life easier for people.	1 = Strongly Disagree, 7 = Strongly Agree	Suh and Ahn (2022)

	33. AI has a connection to my life. 34. I will use AI to find solutions for problems that I face every day. 35. AI helps me in real-world problem-solving. 36. In the future, AI will be essential to my life. 37. Everyone needs AI. 38. AI produces more benefits than drawbacks. 39. AI needs further investigation. 40. In my opinion, most careers in the future will require knowledge of AI.		
Student's Attitudes toward AI *(Behavioural components)*	41. The field of AI is the place I want to work. 42. I will choose a position in the AI industry. 43. If there were a club about AI, I would join it. 44. I enjoy employing AI-related objects. 45. Learning about AI is enjoyable. 46. I wish to keep learning more about AI. 47. I am interested in watching videos online on AI. 48. Using AI, I want to create something that makes life easier for people. 49. The development of AI interests me.	1 = Strongly Disagree, 7 = Strongly Agree	Suh and Ahn (2022)

	50. The use of AI is interesting. 51. There should be more time spent discussing AI in class. 52. I am knowledgeable about AI.		
Perceived usefulness of an AI Lecturer	6. My learning experience would improve if I used an AI lecturer. 7. My ability to study more effectively would increase if I used an AI lecturer. 8. My studies would be easier if I have an AI lecturer. 9. I could use an AI lecturer to coach me for my coursework. 10. I could complete tasks faster in my study if I have an AI lecturer.	1 = Strongly Disagree, 7 = Strongly Agree	Davis (1989)
Ease of communication with AI Lecturer	5. With an AI lecturer, learning how to communicate with it would be simple. 6. An AI lecturer wouldn't require much of my mental effort to interact with. 7. My communication with the AI lecturer would be simple and clear. 8. I think interacting with an AI lecturer would be flexible.	1 = Strongly Disagree, 7 = Strongly Agree)	Davis (1989)
Attitude toward using AI Lecturer	6. Utilizing an AI lecturer increases the standard of my study. 7. I have more control over my study when I have an AI lecturer.	1 = Strongly Disagree, 7 = Strongly Agree)	Davis (1993)

	8. I can learn more effectively than I otherwise could because of the AI lecturer. 9. I believe that with some adjustments, the AI lecturer could be even more user-friendly for me. 10. Having an ai lecture can learn more technical skill.		
Intention to adopt AI Lecturer	7. If there was an online course with an AI lecturer, I would consider taking it. **8.** I would be interested in participating in an online course that uses an AI Lecturer.	1 = Strongly Disagree, 7 = Strongly Agree	Choi and Ji (2015)
	9. I intent to register courses with AI Lecturer. 10. I would like to have AI Lecturer as my lecturer. 11. I would recommend to my friends to have AI Lecturer. 12. It is likely that I will register in courses that with AI Lecturer.		Kim et al. (2010)

Appendices 4.1: Responder's Profile

Profile	Sample (N=252)	Percentage
Gender		
Female	155	61.50%
Male	97	38.50%
Education Level		
Degree	238	94.40%
Postgraduate	14	5.60%
Year Semester		
Year 1	32	12.70%
Year 2	73	29%
Year 3	101	40.10%
Year 4	46	18.30%
Type of University		
Private University	208	82.50%
Public University	44	17.50%
Faculty		
Medical	19	7.54%
Pure Science	25	9.92%
Social Science	189	75%
Other	19	7.54%
Race		
Chinese	185	72.60%
Malay	30	12.30%
Indian	35	14.30%
Other	2	0.80%
Result (CGPA)		
Above 3.0	161	63.90%
2.0 - 3.0	87	34.50%
Below 2.0	4	1.60%
Have you ever taken a class taught by a non-human lecture?		
Yes	105	58.30%
No	147	41.70%

Source: Developed for the research.

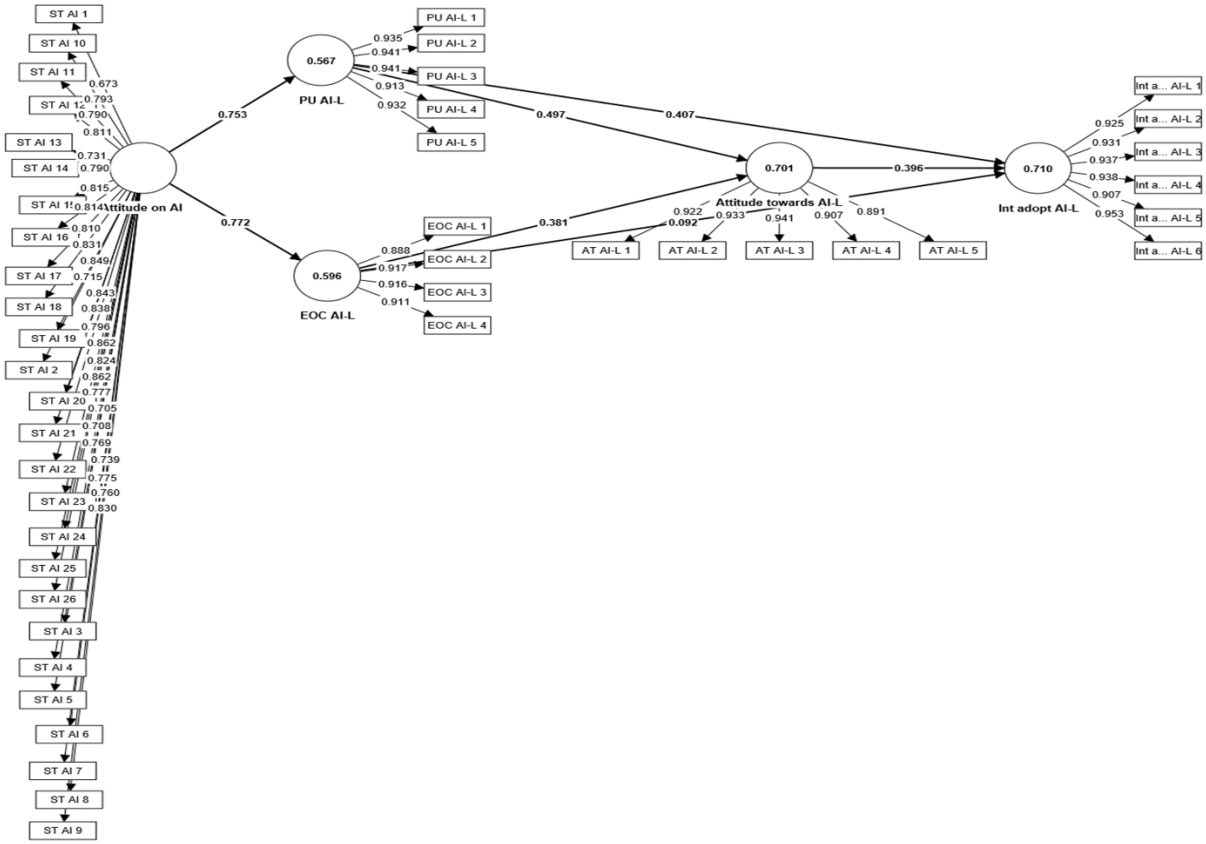
Appendices 4.2: The results of reflective measurement model evaluation

Construct	Items	Factor Loading	Cronbach's Alpha	Composite Reliability (rho_a)	Composite Reliability (rho_c)	Average Variance Extracted (AVE)
Attitude towards AI-Lecturer	AT AI-L 1	0.922	0.954	0.954	0.965	0.845
	AT AI-L 2	0.933				
	AT AI-L 3	0.941				
	AT AI-L 4	0.907				
	AT AI-L 5	0.891				
Ease of communication with AI Lecturer	EOC AI-L 1	0.886	0.929	0.929	0.949	0.824
	EOC AI-L 2	0.918				
	EOC AI-L 3	0.916				
	EOC AI-L 4	0.912				
Intention to adopt AI-Lecturer	Int adopt AI-L 1	0.925	0.970	0.971	0.975	0.869
	Int adopt AI-L 2	0.932				
	Int adopt AI-L 3	0.937				
	Int adopt AI-L 4	0.938				
	Int adopt AI-L 5	0.906				
	Int adopt AI-L 6	0.953				
Perceived usefulness of AI Lecturer	PU AI-L 1	0.935	0.963	0.963	0.971	0.870
	PU AI-L 2	0.94				
	PU AI-L 3	0.941				
	PU AI-L 4	0.914				
	PU AI-L 5	0.933				
Student's attitudes towards AI Lecturer	ST AI 1	0.673	0.976	0.977	0.977	0.625
	ST AI 10	0.793				
	ST AI 11	0.790				
	ST AI 12	0.811				
	ST AI 13	0.731				
	ST AI 14	0.790				
	ST AI 15	0.815				
	ST AI 16	0.814				
	ST AI 17	0.810				
	ST AI 18	0.831				
	ST AI 19	0.849				

ST AI 2	0.715
ST AI 20	0.843
ST AI 21	0.838
ST AI 22	0.796
ST AI 23	0.862
ST AI 24	0.824
ST AI 25	0.862
ST AI 26	0.776
ST AI 3	0.705
ST AI 4	0.708
ST AI 5	0.769
ST AI 6	0.739
ST AI 7	0.775
ST AI 8	0.760
ST AI 9	0.830

Source: Developed for the research.

Appendices 4.3: Measurement Model Evaluation



Source: Developed for the research.

Appendices 4.4: HTMT Discriminant Validity criteria

	Attitude on AI	Attitude towards AI-L	EOC AI-L	Int adopt AI-L	PU AI-L
Attitude on AI					
Attitude towards AI-L	0.782				
EOC AI-L	0.811	0.835			
Int adopt AI-L	0.764	0.828	0.774		
PU AI-L	0.775	0.842	0.862	0.830	

Source: Developed for the research.

Appendices 4.5: The results of the Structural Model Evaluation

	VIF	f2		R-square	R-square adjusted
Attitude on AI -> EOC AI-L	1.000	1.476	**Attitude towards AI-L**	0.701	0.698
Attitude on AI -> PU AI-L	1.000	1.312	**EOC AI-L**	0.596	0.594
Attitude towards AI-L -> Int adopt AI-L	1.000	1.744	**Int adopt AI-L**	0.636	0.634
EOC AI-L -> Attitude towards AI-L	2.979	0.162	**PU AI-L**	0.568	0.566
PU AI-L -> Attitude towards AI-L	2.979	0.278			

Source: Developed for the research.

Appendices 4.6: Structural Model

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	Supported
H1: Attitude on AI -> PU AI-L	0.753	0.756	0.037	20.18	0.000	Supported
H2: Attitude on AI -> EOC AI-L	0.772	0.773	0.037	20.89	0.000	Supported
H3: PU AI-L -> Attitude towards AI-L	0.497	0.499	0.096	5.196	0.000	Supported
H4: EOC AI-L -> Attitude towards AI-L	0.381	0.38	0.09	4.217	0.000	Supported
H5: PU AI-L -> Int adopt AI-L	0.407	0.402	0.114	3.562	0.000	Supported
H6: EOC AI-L -> Int adopt AI-L	0.092	0.094	0.096	0.960	0.169	Not Supported
H7: Attitude towards AI-L -> Int adopt AI-L	0.396	0.399	0.112	3.519	0.000	Supported

Source: Developed for the research.