ADOPTION OF AI TECHNOLOGY IN EDUCATION AMONG UTAR STUDENTS: THE CASE OF CHATGPT

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BY

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DECEMBER 2023

DECLARATION

I hereby declare that:

(1) This undergraduate FYP is the end result of my own work and that due knowledgement has 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 11341.

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DEDICATION

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LIST OF ABBREVIATION

AI	Artificial Intelligence
ML	Machine Learning
UTAR	Universiti Tunku Abdul Rahman
UTAUT	Unified Theory of Acceptance and Use of Technology
TAM	Technology Acceptance Model
TPB	Theory of Planned Behaviour
TRA	Theory of Reasoned Action
PLS-SEM	Partial Least Square SEM
SEM	Structural Equation Modelling
AVE	Average Variance Extracted
HTMT	Heterotrait-Monotrait
VIF	Variance Inflated Factors
R2	Coefficient of Determination
PEX	Performance Expectancy
EE	Effort Expectancy
SI	Social Influence
PE	Perceived Entertainment
PR	Perceived Risk
AB	Adoption Behavior
AU	Actual Usage

PREFACE

AI has significantly affected various industries, including education. Nowadays, many universities have utilized ChatGPT to support staff and improve student learning experiences. ChatGPT is a powerful technology since it can produce cogent, orderly, and human-like responses by using natural language processing. People are using it for writing computer code, editing papers, and writing essays. However, there is limited research on its usage and perception in the context of higher education. It is important to understand students' adoption behavior and perceptions about technology. In addition, there is also limited research on students' performance investigations of AI technology in the higher education sector. Understanding students' opinions and experiences is important to ensure its effectiveness when students use ChatGPT in their learning process. With that, this study will aim to investigate the factors that influence students' adoption behavior on ChatGPT in their learning process and whether ChatGPT can improve their learning outcomes.

ABSTRACT

AI has significantly affected various industries, including education. Nowadays, many universities have utilized ChatGPT to support staff and improve student learning experiences. This study will aim to investigate the factors that influence students' adoption behavior on ChatGPT in their learning process and whether ChatGPT can improve their learning outcomes. Hence, the Unified Theory of Acceptance and Use of Technology (UTAUT) model was applied to investigate adoption of AI technology in education among UTAR students. Using the UTAUT model as a reference, performance expectancy, effort expectancy, social influence, perceived entertainment, perceived risk, adoption behavior, usage be the response. Six hypotheses were developed to identify the relationship between the variables. Questionnaires were prepared using Google Form and distributed to 200 respondents who had used ChatGPT in their learning process. The data collected from respondents were decoded and analysed by using SmartPLS version 4 software. Not only that, theoretical and managerial implications were proposed with the hope that future researchers and practitioners can serve as a reference for the experimental method to further understand students' adoption behavior towards ChatGPT in their learning process.

CHAPTER 1: RESEARCH OVERVIEW

1.0 Introduction

This chapter outlines the research background, problem statement, research questions, research objectives, as well as the significance of the study.

1.1 Research Background

Recent advancements in artificial intelligence (AI) such as machine learning (ML) have given rise to a number of applications in a variety of fields, including education (Zawacki- Richter et al., 2019). In the field of education, it has already had a significant impact, particularly on administration, learning, and teaching (Chen et al., 2020). Universities are increasingly looking into how to use AI to support staff in their teaching and research activities and improve the student experience (Zawacki-Richter et al., 2019).

Bengio et al. (2021) claimed that by employing huge amounts of data, AI systems can be educated to mimic the human brain and do everyday tasks. According to Chatterjee and Bhattacharjee (2020), AI can assist in capturing a special teaching strategy for meeting each student's specific demands. To enhance the learning motivation and success of students in higher education, an e-learning system was also included in the methods of artificial intelligence (Fu et al., 2021).

Recently constructed conversational chatbot ChatGPT from OpenAI may make it simpler for teachers to incorporate AI into their lessons. ChatGPT produces responses to user input that resemble human responses using natural language processing (NLP). It has drawn interest from all over the world due to its excellent performance in producing answers that are cogent, orderly, and instructive (Zhai, 2022). ChatGPT has amassed millions of active consumers globally since its introduction in November 2022, making it the platform with the highest growth rate ever (Hu, 2023). ChatGPT can produce complex text and hold persuasive dialogues with users. Writing computer code, editing papers, and writing essays are just a few of the things it may assist with (Owens, 2023). As ChatGPT continues to acquire additional data from user interactions, its capabilities are anticipated to dramatically increase (Eva et al., 2023).

In the world of education, ChatGPT was met with both adoration and opposition. Similar to calculators and computers that have become normal in arithmetic and science, certain authors think that AI-based programmes like ChatGPT will unavoidably become an essential part of writing (McMurtrie, 2023). In order to support teaching and learning, some advocate using these technologies with students and teachers rather than forbidding them (Sharples, 2022). As a result, ChatGPT can aid students in developing a variety of skills, including writing, reading, data analysis, critical thinking, problem-solving, creating practise problems, and investigation. It empowers learners who have disabilities and enables group and distant learning (Kasneci et al., 2023). In this regard, ChatGPT has the power to completely alter the way students and teachers communicate, acquire knowledge, and work together. The adoption of ChatGPT has resulted in conversations about its consequences and the value of ethical usage in academics, drawing comparisons with earlier technical developments.

According to Fam (2023), Malaysia would not prohibit students at regional higher education institutions from using ChatGPT, according to Minister of Higher Education Datuk Seri Mohamed Khaled Nordin. He highlighted that students must comply with the Department of Higher Education's rules, which have already been printed and given to nearby colleges and universities. Universiti Tunku Abdul Rahman (UTAR) also invites speakers to give some talk on AI technology and ChatGPT. The talk's main goals were to help participants recognise important AI concepts and their potential effects, create a variety of content using prompts and format it in different ways, use ChatGPT to summarise key learning concepts, and use ChatGPT for effective research and assignment completion (UTAR News, n.d.)

However, according to Rudolph et al. (2023), the adoption of AI technology in higher education, such as ChatGPT, has provoked contentious discussions. In this case, some detractors claim that it promotes plagiarism and others assert that it can greatly enhance student-faculty engagement and make it easier for students to get the information they need to succeed academically (Baidoo-Anu & Owusu Ansah, 2023). A steady stream of fresh studies and findings is what keeps the conversation about the benefits and risks of AI in higher education alive. Additionally, ChatGPT works in different ways from search engines such as Google because it only has access to knowledge that was collected prior to September 2021 and does not constantly update for new information. The fact that its factual precision is inconsistent has thus been regarded as a significant shortcoming (Rudolph et al., 2023).

The challenge that ChatGPT will present to education in this instance is likely academic honesty (Kasneci et al., 2023). Several studies revealed on ChatGPT's test question-answering capabilities. Susnjak (2022) evaluated ChatGPT's capacity to produce human-like answers to challenging university-level queries across a range of fields in a preprint. Undergraduate students were the target audience for ChatGPT's creation of difficult critical thinking questions about education, machine learning, past events, and marketing. ChatGPT was requested to come up with the questions, and then provide and analyse the replies. The author assessed ChatGPT's comments according to their originality, accuracy, relevancy, clarity, and correctness as well as their depth and breadth, logic, and persuasiveness. He discovered that ChatGPT demonstrated a high level of critical thinking rather than just information retrieval. The comments produced by ChatGPT were adequate in depth and breadth, clear, explicit, relevant, and logically coherent. Especially in tertiary education settings, where such exams are becoming more common, the author came to the conclusion that ChatGPT is a possible risk to the integrity of online exams (Susnjak, 2022).

1.2 Research Problem

The existing research on AI-based ChatGPT utilization in the education sector is very limited due to its novelty. This study contributes significantly to the body of knowledge on the adoption of cutting-edge educational technologies by examining ChatGPT, a novel AI-based tool for students. Additionally, there is a lack of research in the literature on how ChatGPT is adopted by students for educational purposes (Tiwari et al., 2023). The actual usage, consequences, and perception of ChatGPT in higher education sector have received minimal attention in the literature, according to several research (Rudolph et al., 2023; Zhai, 2022; Qadir, 2022). The gap indicated in the "teaching, learning, and scholarly research" portion of the previously mentioned research (Dwivedi et al., 2023) is arguably the most important one for this paper.

In short, there is limited research base on the AI technology implication in education sector. In this case, this study fills the gap by identifying ChatGPT adoption drivers in education. This study examines the effects of ChatGPT in higher education as a result of student adoption and perception of the technology. This issue is extremely important since it has the potential to have significant effects on academic integrity, teaching, and learning in the higher education industry (Ventayen, 2023).

In addition, according to Lo (2023), further study and development are required to fully understand ChatGPT's potential impact on the education industry because it is still in the early stages of use in education. Future research will center on the question of whether ChatGPT can offer students a better educational experience and academic performance. If so, what are the students' opinions and experiences. To ensure ChatGPT's effectiveness and seamless integration into higher education institutions and identify its drawbacks and benefits, it is crucial to comprehend how it is seen and why students utilize it (Qadir, 2022). In conclusion, there is limited research base on how AI technology implication will affect the students' academic performance. In this case, this study fills the gap by identifying whether the students' academic performance will be enhanced after using ChatGPT in their learning process.

1.3 Research Objectives & Research Questions

By filling in the gap in the literature on ChatGPT's adoption (and consequently, the resulting consequences on students' learning process and experience), this research seeks to provide to the increasing body of study in this field. This study aims to offer a greater knowledge of the inherent advantages, drawbacks, and applications of ChatGPT in higher education sector by constructing on the existing literature and filling the research gap.

To fulfill this objective, the study aims to achieve the following goals:

1. Investigate the students' adoption behavior with ChatGPT in their learning process and the factors that will impact on their adoption behavior.

2. Examine how students perceive ChatGPT's influence on their educational experiences, paying particular attention to factors like academic achievement, learning effectiveness, and motivation.

3. Discuss strategies for students, educators, and institutions to use ChatGPT in education, studying, and evaluation practices, taking into account the advantages and disadvantages that have been noted.

Taking the objectves into consideration, the research question that guiding this study is:

1. How do students perceive ChatGPT in the context of learning?

2. What is the impact of ChatGPT on students' learning experience?

1.4 Research Significance

The potential for this study to promote education at UTAR is one of the main justifications for its importance. The education institution can find opportunities to improve the educational experience by thoroughly studying how UTAR students use AI technology in their learning process. This knowledge can play a critical role in guiding the creation of instructional resources, tools, and methods based on AI that are tailored to the unique requirements and preferences of UTAR students.

Second, the research shows promise for improved learning outcomes and instructional strategies. It is feasible to determine which AI applications are most successful and where changes are required by identifying trends in AI usage. This information may enable UTAR lecturers to make better use of AI technology, resulting in a more stimulating and effective learning environment.

However, for educational institutions such as UTAR, resource allocation is a crucial challenge. Due to limited resources, wise investments are required, and this research might be crucial in maximizing resource allocation. Understanding how students use AI will help UTAR deploy its funds more effectively, putting money into projects that are more likely to be adopted by students and yield a higher return on investment.

Additionally, pedagogical innovation is necessary to maintain a leading position in education. The results of this study can motivate creative teaching and learning strategies at UTAR. Educational institutions can use this knowledge to explore fresh approaches for incorporating underused AI capabilities into the curriculum, establishing a culture of pedagogical creativity.

Finally, this study has the potential to significantly advance the state of knowledge on the use of AI in education. Its conclusions can help UTAR and other educational institution by offering insightful information on the best practises, difficulties, and opportunities related to integrating AI in educational settings.

In summary, this study is significant to UTAR as well as other educational institutions. This study will give all the education institutions a comprehensive picture of how the ChatGPT affects students' learning outcomes as well as how they perceive the ChatGPT.

1.5 Conclusion

This chapter has provided an overview of the AI technology especially ChatGPT. Undeniably, ChatGPT received significant attentions after it launched. This technology can generate human-liked answer and in depth and breadth, clear, explicit, relevant, and logically coherent response. Thus, students should take this advantage to improve their academic performance as well as the learning process. Hence, these have inspired the researcher to study and explore what factors will lead students to have a adoption behavior and usage towards ChatGPT. This study focuses on the UTAR students. In conclusion, this study aims to provide insightful contributions with useful information and outputs to UTAR and other educational institutions.

CHAPTER 2: LITERATURE REVIEW

2.0 Introduction

In order to establish the theoretical groundwork for the study, Unified Theory of Acceptance and Use of Technology (UTAUT) model will be adopted. The relationships between both independent and dependent variables will be investigated using these theories. Additionally, the relevant variables will be completely evaluated and discussed using data from earlier studies emphasizing AI technology and its implications on the education sector.

2.1 Underlying Theories

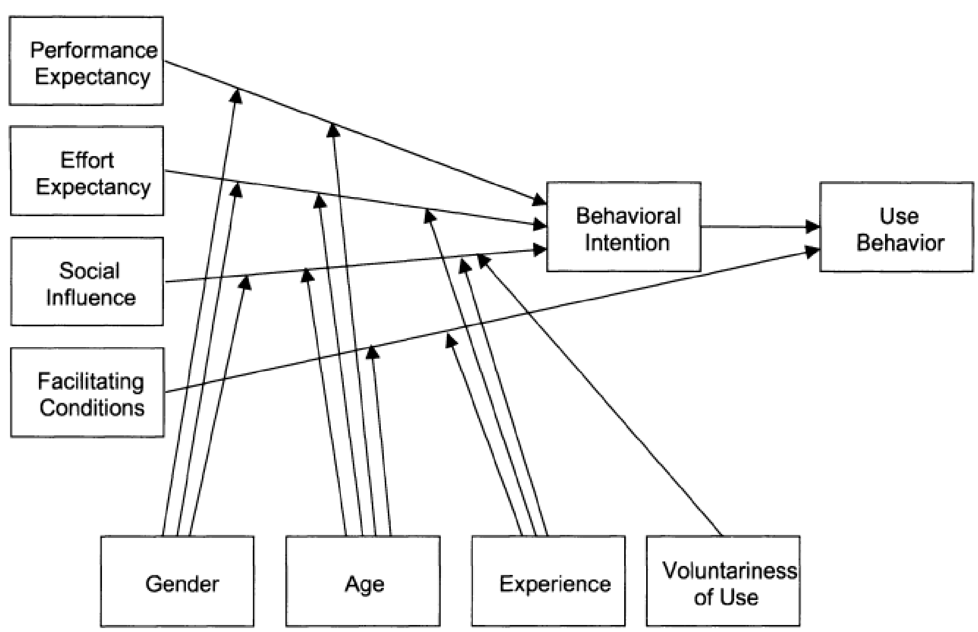
This study will adopt Unified theory of acceptance and use of technology (UTAUT) model.

2.1.1 Unified theory of acceptance and use of technology (UTAUT) model

Venkatesh et al. (2003) proposed the UTAUT model, which primarily incorporates relevant models and data from many domains. It mainly integrates the eight theories which include TAM (Davis, 1986; Venkatesh & Bala, 2008), social cognitive theory (Compeau & Higgins, 1995), the model of PC utilisation, task-technology-fit (Goodhue & Thompson, 1995), the Theory of Planned Behaviour (TPB) (Ajzen, 1985),the motivational model (Davis et al., 1992), innovation diffusion theory (Moore & Benbasat, 1991), TRA (Fishbein & Ajzen, 1977), and the combination of TPB as well as TAM. One of the most important factors is one of the model's four key principles, which include performance expectancy, effort expectation, facilitating conditions, and social influence.

Empirical research has shown that the UTAUT, having up to 70% explanatory power, proves more convincing than earlier models. This idea has been employed by the academic community to support numerous outstanding hypotheses. Mehta and Morris et al. (2019) used UTAUT as a starting point to apply the unique conceptual model to the setting of digital education by merging human values with technological adoption models. Nie et al. (2020) investigate the evidence of TPB and offer a deeper comprehension of individual behaviour in technology adoption and human-computer interaction. The application domains of study have also become increasingly varied as a result of developments in science and technology. UTAUT has been considered the best model for mobile learning and is suitable in the setting of mobile learning and technology (Venkataraman & Ramasamy, 2018). In this study, performance expectancy, effort expectancy and social influence will be utilized. Figure 2.1 shows the model of UTAUT.

Figure 2.2: Unified theory of acceptance and use of technology (UTAUT) model



Source: Venkatesh et al. (2003)

2.2 Review of Variables

2.2.1 Performance Expectancy

The degree to which a person expects that utilizing the system would enable him or her to improve their performance in the workplace is known as performance expectancy. Since this model is a combination of earlier ones, five elements from earlier models including perceived usefulness from TAM, external motivation from motivational model, job fit from PC utilisation model, relative advantages from innovation diffusion theory, and outcome expectations in social cognition theory which helped in the formation of the performance expectancy variable (Davis et al., 1989; Venkatesh et al., 2003). In their studies, these researchers claimed that performance expectancy represents a crucial concept that affects the adoption and ultimate use of information systems. As a result, it may also be said that performance expectancy has an immediate impact on the way UTAR students use AI technology like ChatGPT. This is to ensure UTAR students can get the knowledge they need to succeed in their studies and academic achievements. Therefore, a UTAR student may be inclined to use ChatGPT if they believe it will help them significantly improve their academic achievement.

2.2.2 Effort Expectancy

The level of convenience perceived for utilising a system is known as effort expectancy. Perceived ease of use from technology adoption model, complexity in PC utilisation model, and innovation diffusion theory are comparable constructs in different models and theories from a conceptual perspective (Davis et al., 1989; Venkatesh et al., 2003; Venkatesh & Davis, 2000).

In this instance, the adoption of AI technology by UTAR students is directly related to effort expectancy. This is due to the likelihood that UTAR students' use of AI technology will depend on how simple or difficult it is to use ChatGPT to quickly acquire pertinent information. Therefore, if UTAR students discover that using ChatGPT in their learning process is quite simple, they might not hesitate to use it.

2.2.3 Social Influence

According to Venkatesh et al. (2003), social influence refers to how much a person thinks other people matter to him or her when utilizing a new technology. This variable's construction was influenced by the concepts of subjective norms which are rational action theory, planned behavior theory, decomposed planned behavior theory, and TAM 2, social factors in PC utilization model, and image in innovation dissemination theory. Additionally, social influence is the extent to which a customer's social circle such as their family, friends, and coworkers accepts the use of AI devices in performing services as appropriate and consistent with group norms. For instance, Gursoy et al. (2017) discovered that one of the most significant sources of information when a consumer's decision-making process is family and friends. Similarly, Jeon et al. (2018)'s findings show that people tend to embrace the culture, values, and norms of their social groups as their own and adjust their behavior as a result. Furthermore, following a group's behavioral norms will increase an individual's attachment level of belongingness to that group, based on the Social Identity Theory (Tajfel & Turner, 1979).

Therefore, in this study, employing AI technology will be advantageous to UTAR students' social identities if their social network, such as friends and family, have positive thoughts and attitudes towards its usage in education and learning. Thus, if their friends, family, and other significant individuals influence them, UTAR students will be more inclined to use ChatGPT.

2.2.4 Perceived Risk

The concept of perceived risk was developed by Bauer (1960), and it has psychological underpinnings. The perceived risk was split by Cunningham (1967) into uncertainty and repercussions (the severity of the harm caused by the product not living up to expectations). The perceived risk is higher if the client places more emphasis on the harmful degree. The focus of this study is on the features of AI-enabled online educational programs that demand user data collecting. Consumers are becoming more concerned about user privacy as a result of the Internet's many practical applications. The largest obstacle to the development and improvement of AI products in recent years has been the violation of user privacy. There are privacy and ethical concerns that should be taken into consideration when applying AI technology to the study of educational data. As a result, issues with privacy and data protection could come up and need to be carefully examined (Chen et al., 2020). Finance is a major source of privacy and security issues when it comes to AI products, especially when it comes to sensitive personal information like credit card numbers and purchase history. Users are aware of this danger when utilizing AI products. The concepts of psychological risk and financial risk are thus included among the perceived risk variables evaluated in this study. People are more inclined to adopt an AI product if there is no perceived danger associated with it.

2.2.5 Perceived Entertainment

According to Davis et al. (1992), perceived entertainment is the amount of enjoyment that can be obtained from using the computer itself. It relates to the enjoyment brought on using technology (Dennis et al., 2007). The user's enthusiasm for using the product is positively associated with the interface's entertainment value, hence it is crucial to consider this when creating and designing a product. Therefore, the user's interest in the interface will be stimulated if the developer can make it interesting. As a result, people will enjoy utilizing it and be more inclined to do so. According to Dennis et al. (2007), user acceptability and adoption behavior are largely determined by the functional and entertaining qualities of products and systems. According to Feng et al. (2015), users' learning behavior may be positively impacted by their impression of amusement. Therefore, UTAR students are more likely to embrace and use ChatGPT consistently if they believe that using it in their learning process is enjoyable and interesting.

2.2.6 Adoption Behavior

Numerous studies have demonstrated that behavioral intentions influence behavior in an effective manner and that there is a direct connection between intention and behavior as well as the process by which people go from making decisions to carrying them out in the real world. Chau (2019) found that performance expectancy, effort expectancy, perceived entertainment, and perceived risk had a significant and favorable influence on adoption behavior. Additionally, Koenig-Lewis et al.'s (2015) study found that social influence had a considerable impact on adoption behavior, indicating that people's acceptance of digital wallets is heavily influenced by their peers' opinions. All of the independent variables in this study, such as performance expectancy, will therefore result in adoption behavior. For instance, if UTAR students discovered that ChatGPT had helped them succeed academically, they would want to adopt it and use it frequently.

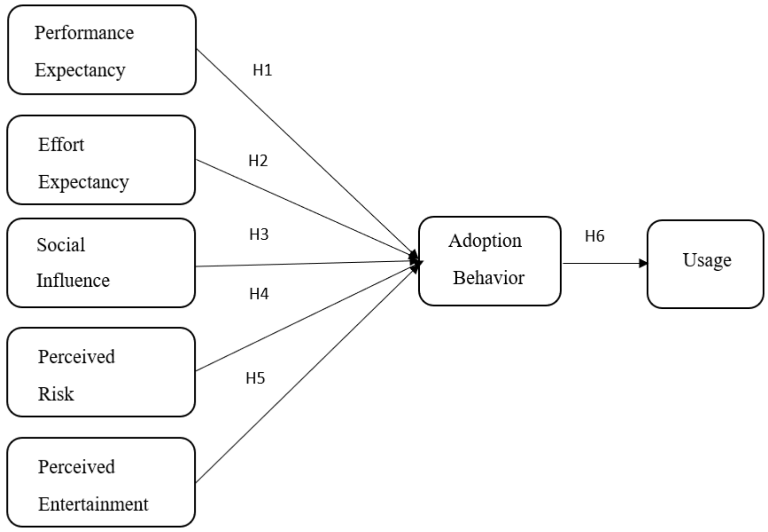
2.2.7 Usage

The term "actual technology usage" will be used from now on. The phrase "technology use" in TAM actually refers to the same behaviour as the term TRA, but in a technological environment. Intensity and usability have a direct impact on this construct. The goal of the user's behaviour and their level of assurance that ChatGPT will enhance learning outcomes determine how much ChatGPT is used (Harris, 2017). According to Dwivedi et al.'s 2019 study, adopting behaviour directly affects usage. It follows that UTAR students are more likely to use ChatGPT if they have the aim to incorporate it into their learning process.

2.3 Conceptual Framework

According to Adom (2018), the conceptual framework demonstrates how the key ideas under study are related to one another. Figure 2.3 below depicts the study's conceptual framework, which explains the factors affects the adoption behavior and usage of AI Technology among UTAR students. Independent variables are performance expectancy, effort expectancy, social influence, perceived risk, and perceived entertainment while adoption behavior serve as mediator. Usage is stated as the dependent variable.

Figure 2.3: Conceptual Framework



Source: Developed for the research

2.4 Hypotheses Development

2.4.1 Relationship between Performance Expectancy and Adoption Behavior

The UTAUT claims that performance expectancy is the primary variable that directly influences consumers' willingness to employ a product (Li et al., 2016). The performance expectancy denotes the extent to which the system enhances academic performance in the context of the employment of AI technology. This study defines performance expectancy in the context of using ChatGPT, an AI technology, therefore the performance expectancy suggests that users can improve the effectiveness of their learning. Particularly in the context of artificial intelligence, learning, and knowledge access are frequently utilised. According to this analysis, users' willingness to use technology will rise when they believe it will benefit them or better their own work and academic achievement. Therefore, in accordance with the findings of earlier research, this study proposes the following hypothesis:

H1: There is a significant relationship between performance expectancy and adoption behavior.

2.4.2 Relationship between Effort Expectancy and Adoption Behavior

Users do not want to spend a lot of time or effort learning a new system, in accordance with effort expectancy (Li et al., 2016). The ease of use of the AI-enabled online education goods is another aspect of the effort expectancy. Wong et al. (2015) stated that effort expectancy is consistently acknowledged as a crucial determinant of user adoption behavior. Yang (2015) conducted a study based on survey data gathered from US university students to examine the behavioral intentions of young customers in purchasing mobile shopping apps. The results showed that effort expectancy provided an accurate predictor of whether mobile shopping apps would be used. The user will more likely to use technology if the level of complexity of the technology decreases. Therefore, it is expected that effort expectancy will have an impact on adoption behavior, and the following hypothesis have been given.:

H2: There is a significant relationship between effort expectancy and adoption behavior.

2.4.3 Relationship between Social Influence and Adoption Behavior.

Customers tend to install the same applications as a reference group, such as friends, family, or a colleague, in order to converse and exchange knowledge with them (Chua et al., 2018). The degree to which people believe that important others, such as friends or family, think they should adopt a technology, is referred to as social influence. The interactive impact of social influence on users' adoption behaviour towards recycling practises was validated in the most recent study by Wan et al. (2017). According to Liébana-Cabanillas et al. (2018), users typically act in a certain way to live up to the expectations of their family, friends, and the wider community. Tan and Ooi (2018) claimed that social influence may have an impact on consumers' views and values and that people respond to social pressure by behaving in certain ways. According to Madan and Yadav's (2018) research, consumers think about what their friends and family think before utilizing mobile devices and are less likely to adopt new technologies if such opinions are unfavorable. Consequently, the following hypotheses could be developed based on the research's findings and the outcomes of previous studies:

H3: There is a significant relationship between social influence and adoption behavior.

2.4.4 Relationship between Perceived Risk and Adoption Behavior.

According to Farivar et al. (2018), perceived risk refers to users' perceptions of possible undesirable results or the unpredictability of outcomes or repercussions. According to research from Indiani et al. (2015) and Zulfikar & Mayvita (2018), perceived risk has a greater influence on actual usage.

Additionally, a study indicated that the intention to use mobile banking is negatively and significantly impacted by the perception of risk (Mahardika & Giantari, 2020). Additionally, multiple earlier studies in these diverse categories have demonstrated the adverse effects of risk on behavioural intention for telemedicine services (Kamal et al. 2020), restaurant visits (Lee et al. 2019), and online shopping channels (Slade et al., 2015; Tran 2020). People tend to avoid circumstances that are unknown and confusing when they feel uncomfortable with them. According to this study, UTAR students are less likely to use ChatGPT if they consider it as carrying a significant level of risk. As a result, the following hypothesis have been proposed based on previous studies:

H4: There is a significant relationship between perceived risk and adoption behavior.

2.4.5 Relationship between Perceived Entertainment and Adoption Behavior.

Perceived entertainment was defined by Venkatesh et al. (2012) as joy, delight, and amusement. or liveliness experienced while using a technology and researchers discovered that it had a substantial influence on customers' acceptance of new technology. In this study, perceived entertainment refers to how much a person finds utilizing ChatGPT to be pleasurable. Perceived entertainment has been used in certain e-learning research to explain how it affects students' IT adoption behavior, and it has been found to dramatically boost university students' usage intentions. Students are more likely to have a favourable attitude towards the usability and usefulness of an e-learning system when they use it and enjoy it (Cabada et al., 2017). Additionally, a stronger perception of enjoyment from utilizing new technology may reduce worry, which would then increase confidence (Koenig-Lewis et al., 2015). Therefore, in this study, UTAR students tended to use ChatGPT if they thought doing so was enjoyable. On the basis of the prior research, the following hypothesis can be made:

H5: There is a significant relationship between perceived entertainment and adoption behavior.

2.4.6 Relationship between Adoption Behavior and Usage.

Yi et al. (2016) claimed that adoption behavior is the irrational likelihood of engaging in a behavior that results in usage intention. The intensity with which people use technology is known as usage behavior (Awwad and Al-Majali, 2015). Behavioral intention is an assessment of the reason of people choose to engage in or carry out a specific conduct (Ajzen & Fishbein, 1980). Therefore, it is necessary to first assess the consumer's behavioral intention before deciding whether UTAR will accept and apply the ChatGPT in their learning process. The usage behavior includes a very important component called behavioral intention (Awwad and Al-Majali, 2015). Williams et al.'s (2015) review of the literature revealed that many technology adoption models are created to explain the behavior of technology users. The reason for this is that customer use behaviour is the best indicator of actual technology utilization. It has been demonstrated by earlier studies (Wong et al., 2015; Rezaei, 2017) pertaining to mobile technologies. Emon et al. (2023) found a substantial and significant correlation between ChatGPT adoption behaviour and usage. As a result, the following hypothesis have been proposed based on previous studies:

H6: There is a significant relationship between adoption behavior and usage.

2.5 Conclusion

This chapter covers the definitions of all the variables as well as the underlying theory. For every independent variable, a hypothesis had been developed in addition to the definition of the variable.

CHAPTER 3: METHODOLOGY

3.0 Introduction

The chapter 3 discusses the methodology of this study, including research design, research instrument, sampling design, pilot test, data collection methods, construct instruments, and proposed data analysis.

3.1 Research Design

The study design serves as a manual that explains how the variables connect to one another in order to answer the research objectives and provide the study structure (Baran, 2022).

3.1.1 Quantitative Research

In order to quantify the data while keeping the investigation's goal or objective in mind, quantitative research will be used. Quantitative research is a crucial area in the context of research design. Goertzen (2017) states that acquiring and analyzing structured, statistically representable data is a component of quantitative research methodologies. The adoption of ChatGPT among UTAR students will be investigated through the use of quantitative research in this study. Additionally, surveys can be used to gather information that will be examined and conclusions regarding the study drawn.

3.1.2 Descriptive Research

Descriptive research is characterizing people, events, or conditions by looking at them in their natural settings. The researcher merely explains the sample and/or variables without changing any of the variables. The only model that may investigate a single variable is descriptive research, which can explore several variables (Siedlecki, 2020). Descriptive studies examine the traits of a population, highlight issues within an organization, a group, or a population, or investigate differences in traits or customs between organizations or even nations. Since the 7-point Likert scale in the questionnaire may be used to measure both the dependent and independent variables, the descriptive research methodology was used in this study. Through the gathering of data, this study also tries to investigate and draw conclusions about the relationship between an endogenous variable and exogenous variables. This study is regarded as having descriptive research because it developed hypotheses that could be used to assess correlations between different variables.

3.2 Sampling Design

In order to accomplish the goals of the study, a researcher will employ sampling, according to Sharma (2017), sample size is small number of reference individuals from a pre-defined population to act as subjects for observation.

3.2.1 Target Population

In this study, the target population is UTAR students. There are two campuses for UTAR which are Kampar campus and Sungai Long campus. Therefore, this study will be targeting the students from both campuses. Next, the students will be divided into two groups which include art stream and science stream.

Basically, this study will be targeting UTAR students as the topic is adoption of AI technology in education among UTAR students.

3.2.2 Sampling Techniques

In contrast to random selection, non-probability sampling approaches employ a methodology in which the sample is chosen based on the researcher's subjective judgment (Elfil & Negida, 2017). So, in this study, the researcher will utilize non-probability sampling.

In this case, purposive sampling will also be utilized. The purposeful selection of a participant is a component of the purposive sampling method, which is also known as judgement sampling. This nonrandom technique does not require underlying theories or a predetermined number of participants. Simply defined, the researcher chooses what information is necessary to have and then searches for sources willing and able to supply it based on their knowledge or experience. This includes identifying and choosing individuals or groups of people who are knowledgeable and skilled about an interest phenomenon (Etikan, 2016). In this study, the researcher is going to approach the UTAR students who are studying in art and science stream by distribute the online survey form.

3.2.3 Sample Size

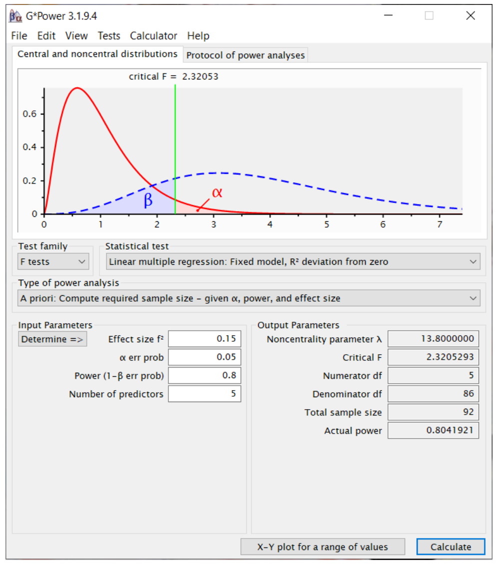
For calculating sample size, Roscoe's (1975) guidelines have been a popular option for the past few decades. According to Roscoe, most behavioral investigations should have a sample size of at least 30 and no more than 500 (Sekaran & Bougie, 2016). Sample sizes beyond 500 may result in Type II errors. The sample size for multivariate data analysis, for instance, regression analysis, need to be ten times larger than the total amount of variables (Roscoe, 1975). Roscoe's guidelines were applied in recent research by Seman et al. (2019), Suki and Suki (2017), and Sultana (2020) to estimate the appropriate sample size. It demonstrates that Roscoe's guidelines are still relevant for current research.

Additionally, according to Hair et al. (2018), the minimal observation-to-variable ratio should be 5:1, although ratios of 15:1 or 20:1 are more desirable. Accordingly, even though a minimum of five respondents must be taken into account for each independent variable in the framework, 15 to 20 samples for each independent variable are strongly advised. Despite the 5:1 ratio seems simple to use, students need to take greater ratios (such as 15:1 and 20:1) into account when choosing the sample size for their own studies. For instance, 90 replies are required if my study has 6 independent variables (15:1 ratio).

Furthermore, recent discoveries imply that researchers should use power analysis to select sample size (Hair et al., 2018; Hair et al., 2019; Uttley, 2019; Ringle et al., 2018; Kline, 2016). By choosing the portion of a framework with the highest number of variables, power analysis establishes the minimal sample size. Calculating the minimal sample size necessary needs knowledge of power significance level, and effect size (Hair et al., 2018). Selecting the "F tests" analysis from the test family selections is the first thing to do once the program is open. Select "Linear Multiple Regression: Fixed Model, R2 Deviation from Zero" from the list of statistical tests. The input data for a mediation model will be effect size = 0.15, alpha= 0.05, and power = 0.80. In this scenario, the researcher inserts "5" as the number of predictors in the input parameters, adhering to the maxim of arrows pointing to one variable in the model. According to G*Power, 92 samples are the minimum amount that is needed for the mediation model. Figure 3.1 shows the G*Power result.

Thus, in this study, by referring to Roscoe's guideline, a sample size of 200 responses is planned to be collected from the UTAR students by using online questionnaires such as Google form.

Figure 3.1 G*Power result



Source: Develop for the study

3.3 Data Collection Methods

It is suggested to use a questionnaire survey to get primary data in order to evaluate the constructed hypothesis. Primary data are facts obtained by researchers themselves. One of the main methods for gathering quantitative data is a questionnaire survey. (Victor, 2017). Since the goal of this study is to determine the impact of AI technology adoption in education among UTAR students, primary data gathering is ideal for this study.

3.4 Research Instrument

In this study, an online questionnaire was developed and distributed to UTAR students. This questionnaire is aimed to examine the adoption of AI technology in education among UTAR students. The question in the questionnaire was adopted from past related journals to ensure the reliable and validity.

The questionnaire was constructed with Section A and Section B, using Google Forms. All of the questions were written as closed-ended questions, making it simple for respondents to choose the best response from the available multiple-choice options.

Demographic data will be gathered for Section A by asking respondents for information on their gender, level of education, year/semester, stream, and race. This part will collect data from a nominal scale to classify the demographic details of the intended respondents.

The link between the use of ChatGPT among UTAR students, the dependent variables, and the six independent variables was examined in section B. Additionally, to evaluate the respondents' level of agreement, ordinal scale data will be gathered using a 7-point Likert scale.

3.5 Construct Instrument

Table 3.1: Construct Instrument

Construct	Adopted Questionnaire	Original Questionnaire	Scale	Source
Performance expectancy	1. Using ChatGPT for my study would enable me to accomplish tasks more quickly. 2. Using ChatGPT would improve my academic performance. 3. Using ChatGPT for my study would	1. Using (application name) in my job would enable me to accomplish tasks more quickly. 2. Using (application name) would improve my job performance. 3. Using (application name) in my job would increase my productivity.	1 = Strongly Disagree, 7 = Strongly Agree	(Venkatesh & Zhang, 2010)

	increase my productivity. 4. Using ChatGPT would enhance my effectiveness on my academic task. 5. Using ChatGPT would make it easier to do my academic task. 6. I would find ChatGPT useful in my academic task.	4. Using (application name) would enhance my effectiveness on the job. 5. Using (application name) would make it easier to do my job. 6. I would find (application name) useful in my job.		
Effort Expectancy	1. Learning to use ChatGPT is easy for me. 2. I think it is easy to get ChatGPT to do what I want it to do. 3. My interaction with ChatGPT would be clear and understandable. 4. I find ChatGPT is flexible to interact with.	1. Learning to operate (application name) would be easy for me. 2. I would find it easy to get (application name) to do what I want it to do. 3. My interaction with (application name) would be clear and understandable. 4. I would find (application name) to be flexible to interact with.	1 = Strongly Disagree, 7 = Strongly Agree	(Venkatesh & Zhang, 2010)

	5. It is easy for me to become skillful by using ChatGPT. 6. I find ChatGPT is easy to use.	5. It would be easy for me to become skillful at using (application name). 6. I would find (application name) easy to use.		
Social Influence	1. People who are critical to me think that I should use ChatGPT. 2. Those who have the power to affect my behaviour believe I should use ChatGPT. 3. Majority of the people surrounding me using ChatGPT.	1. People who are important to me think that I should use mobile banking. 2. People who influence my behavior think that I should use mobile banking. 3. Most people surrounding me use mobile banking.	1 = Strongly Disagree, 7 = Strongly Agree	(Sarfaraz, 2017)
Perceived Risk	1. I am concerned that using ChatGPT would cause information to be compromised, violated, and have my personal information used improperly.	1. I am concerned that using ChatGPT will lead to information leakage, violation and misuse of personal health information. 2. I am concerned about the quality of health information	1 = Strongly Disagree, 7 = Strongly Agree	(Kong et al, 2023)

	2. The accuracy of the academic data collected by ChatGPT worries me. 3. I worry that the academic data I acquire through ChatGPT will fall short of my expectations and I have no idea how to assert my legal rights.	obtained using ChatGPT. 3. I am concerned that the health information obtained through ChatGPT will not meet my expectations and I do not know how to protect my rights.		
Perceived Entertainment	1. I think using ChatGPT is enjoyable. 2. The actual experience of using ChatGPT is pleasant. 3. I enjoy using ChatGPT.	1. I find using (the system's name) to be enjoyable. 2. The actual process of using (the system's name) is pleasant. 3. I have fun using (the system's name)	1 = Strongly Disagree, 7 = Strongly Agree	(Venkatesh et al., 2012)
Adoption Behavior	1. I will keep gathering knowledge on ChatGPT.	1. I will continue to acquire AI-related information. 2. I will keep myself updated with the latest AI applications.	1 = Strongly Disagree, 7 = Strongly Agree	(Chai et al, 2021)

	2. I will stay up with the most recent ChatGPT programs. 3. I intend to use ChatGPT to help me in my academic process. 4. I will keep studying ChatGPT.	3. I intend to use AI to assist with my learning. 4. I will continue to learn AI.		
Actual Usage	1. I will utilise ChatGPT personally while learning. 2. I will use ChatGPT personally as a resource for educational tasks.	1. I will personally use Airlangga University e-Learning Application (AULA) during learning process. 2. I will personally use Airlangga University e-Learning Application (AULA) as a reference for learning activities.	1 = Strongly Disagree, 7 = Strongly Agree	(Rahmawati, 2019)

Source: Developed for the study

3.5.1 Nominal Scale

A categorical variable's diverse values on the nominal scale solely signify various groups of objects. In terms of the demographic aspects of the questionnaire, the most commonly requested question is the respondents' gender, which is a categorical variable (Prabhaker, 2018). The questionnaire will ask about five demographic factors, including gender, education level, year, semester, stream, and race. The categorical variables are these five demographic questions. Therefore, a nominal scale is employed in this study.

3.5.2 Ordinal Scale

According to Prabhaker (2018), the range on a seven-point Likert scale is from strongly disagree to strongly agree. The scale's sections will evaluate respondents' opinions of the performance expectancy, effort expectancy, perceived risks, social influences, perceived entertainment, and adoption behavior that influenced the use of AI technology in education among UTAR students. As a result, this study uses an ordinal scale.

3.6 Pilot Test

A pilot test will be conducted in advance of the primary research study to evaluate the viability of different information-gathering tools and research procedures. The main objective of this pilot test is assessing the effectiveness of the research and make any necessary adjustments (Cleave, 2021). A total of 30 samples were collected for this investigation, and an online questionnaire was used for the test. Table 3.2 shows the Cronbach's Alpha result of this study.

Table 3. 2: Cronbach's Alpha result

Variables	Cronbach's Alpha
Performance Expectancy	0.938
Effort Expectancy	0.954

Social Influence	0.767
Perceived Risk	0.811
Perceived Entertainment	0.923
Adoption Behavior	0.921
Usage	0.929

Source: Develop for the study

All of the variables' values exceed the minimal validation level of 0.70 that is advised (Adeniran, 2019). It shows that every scale is inside a respectable and trustworthy range. As a result, these above-average values have shown that every value within these seven variables has complied with the requirements and is trustworthy enough to be cover in this research for additional analysis.

3.7 Proposed Data Analysis

The reliability test for the pilot test in this study will be conducted using XLSTAT. A statistical programme called XLSTAT can be used to perform multivariate analysis on large sets of complex data (Vidal et al., 2020). Additionally, the researcher will carry out a data regression analysis in SmartPLS to examine the link between exogenous variables and endogenous variables.

3.7.1 Descriptive Analysis

Descriptive analysis helps explain variability, and distribution to enable structures to develop and fit the criteria of the data. By the application of the histogram, table, and chart, descriptive statistics enable a researcher to assess the essential properties of collected data (Kemp et al., 2018).

3.7.2 Reliability Test

One of the most used dependability metrics in the social and organizational sciences is Cronbach's alpha (Cronbach, 1951). Typically, a figure between .00 and 1.0 is represent the value of Cronbach's alpha. A number of 1.0 denotes perfect measurement consistency, while a value of.00 denotes no measurement consistency. Depending on the form of research, a range of 0.70 to 0.90 or higher is considered acceptable (Adeniran, 2019). Figure 3.2 shows Coefficient of Cronbach's Alpha reliability level.

Figure 3.2: Coefficient of Cronbach's Alpha reliability level

No	Coefficient of Cronbach's Alpha	Reliability Level
1	More than 0.90	Excellent
2	0.80-0.89	Good
3	0.70-0.79	Acceptable
4	0.6-0.69	Questionable
5	0.5-0.59	Poor
6	Less than 0.59	Unacceptable

Source: Arof et al. (2018)

3.7.3 Inferential Analysis

Structural equation modelling (SEM) was employed for the inferential analysis with the following rationales. SEM is a multivariate analytical method that evaluates multiple complex relationships between variables at once. In fact, one of the "SEM family members," the Partial Least Square SEM (PLS-SEM), was selected for this investigation. The PLS-SEM will be a better approach if the study is a development of an existing hypothesis (Hair et al., 2011). To improve the UTAUT model's applicability in this regard is one of the study's research objectives.

Additionally, the PLS-SEM is a two-stage analytical process that starts with the evaluation of the measurement model and moves on to the structural model.

The PLS-SEM analysis was carried out using SmartPLS version 4 (Hair et al., 2017). Instead of using Cronbach Alpha, PLS-SEM measures the composite reliability to determine the internal consistency dependability (Hair et al., 2017). Furthermore, the convergent validity is determined by the Average Variance Extracted (AVE), the discriminant validity is determined by the heterotrait-monotrait (HTMT) ratios, and the indicator reliability is determined by the outer loadings (Hair et al., 2017).

The path coefficient, the coefficient of determinant, and the collinearity assessment were investigated for the structural model evaluation. First, to determine whether there is a collinearity problem, the collinearity evaluation is measured using Variance Inflated Factors (VIF). Next, the p-value will be used to determine the significance of the path coefficients and the relationship between the independent and dependent variables. Furthermore, Hair et al. (2017) stated that the Coefficient of Determination (R2) is utilized to figure out the extent to which the independent variables in the model influence the variance of the dependent variable.

3.8 Conclusion

This chapter cover a detailed analysis for this research methodology. This chapter covered the following topics: construct measurement, target population, data analysis techniques, sample size, research instrument (questionnaire design and pilot test), sampling methods, sampling design, data collection method, and sampling design. The data analysis procedures that described the study questionnaire included descriptive analysis, reliability analysis, and inferential analysis.

CHAPTER 4: RESEARCH ANALYSIS AND RESULTS

4.0 Introduction

The results of data analysis were presented in this chapter are based on Chapter 3. The distribution of the Google Form resulted in the collection of 200 responses. After the data is filtered, only 97.5% of the responses (N=195) are useful because 5 respondents have been determined invalid for this study. The actual survey responses, as well as descriptive and inferential analyses, will be reviewed. The acquired data will be subjected to a Smart PLS version 4 data cleaning procedure.

4.1 Descriptive Analysis

Descriptive analysis helps explain variability, and distribution to enable structures to develop and fit the criteria of the data. By the application of the histogram, table, and chart, descriptive statistics enable a researcher to assess the essential properties of collected data (Kemp et al., 2018).

4.1.1 Respondent Demographic Profile

Male respondents are lesser than female respondents, with 107 (53.5%) females and 93 (46.5%) males. 142 (71%) of the total respondents' education level is Bachelor's. Foundation and Postgraduate made up 45 (22.5%) and 13 (6.5%) of the respondents' respective educational levels. There are 70 (35%) respondents were from year 1, 47 (23.5%) from year 2, 65 (32.5%) from year 3 and 18 (9%) from year 4. Responses were collected from art stream and science stream, which include 122 (61%) and 78 (39%) respectively.

Table 4.1: Demographic Profile of Respondents

Profile	Sample (N=200)	Percentage
Gender		
Male	93	46.50%
Female	107	53.50%
Education Level		
Foundation	45	22.50%
Undergraduate	142	71%
Postgraduate	13	6.50%
Year Semester		
Year 1	70	35%
Year 2	47	23.5%
Year 3	65	32.50%
Year 4	18	9%
Stream		
Art Stream	122	61%
Science Stream	78	39%
Race		
Chinese	162	81%
India	23	11.50%
Malay	15	7.50%

Source: Developed for the research

4.1.2 Respondent General Information on Adoption and Usage

Table 4.2: Whether respondents have used ChatGPT in their learning process.

Have you used ChatGPT in your learning process before?		
Yes	195	97.50%
No	5	2.50%

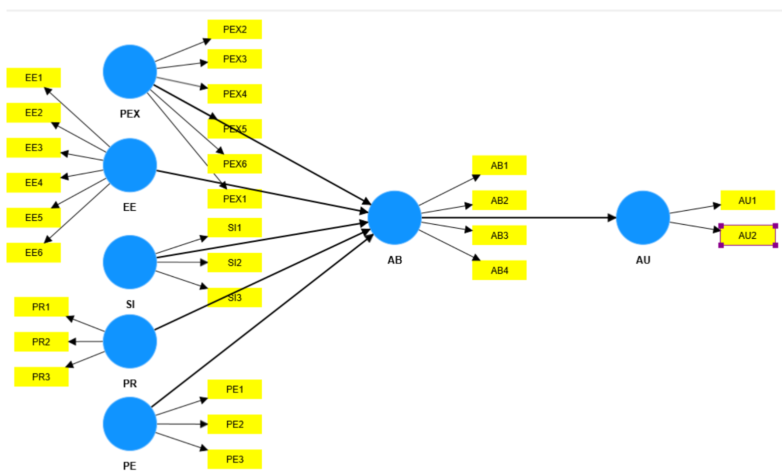
Source: Developed for the research

There were 195 (97.5%) of the respondents used ChatGPT in their learning process before and 5 (2.5%) never used ChatGPT in their learning process before.

4.2 Measurement Model Evaluation

The measurement model evaluation was done in the first stage, and the structural model assessment was done in the second stage.

Figure 4.1: Measurement Model



Source: Developed for the Research

According to Hair et al. (2021), with values greater than 0.708, all of the indicators' outer loadings within each construct are considered acceptable. Table 4.2 displays the factor loadings, which varied from 0.822 to 0.960. As a result, no indicators are excluded from this analysis. According to Hair et al. (2019), reflective measurement models should possess composite reliability (CR) values larger than 0.7, average variance extracted (AVE) values greater than 0.5, and Cronbach's alpha values higher than 0.8. Table 4.3 displays the reflecting measurement model's findings. The AVE value for each element was more than 0.5, and the research approved it. All six structures met the requirements of having an AVE of greater than 0.5 and a CR of greater than 0.7. As a result, all of the constructs satisfied the requirements for reliability and convergent validity.

Table 4.3: Summary of Constructs Reliability and Validity

Construct	Items	Factor Loading	Cronbach's Alpha	Composite Reliability (rho_a)	Composite Reliability (rho_c)	Average Variance Extracted (AVE)
Performance Expectancy	PEX1	0.872	0.925	0.927	0.953	0.870
	PEX2	0.853				
	PEX3	0.894				
	PEX4	0.879				
	PEX5	0.857				
	PEX6	0.853				
Effort Expectancy	EE1	0.847	0.942	0.944	0.954	0.776
	EE2	0.898				
	EE3	0.905				
	EE4	0.874				
	EE5	0.869				
	EE6	0.890				
Social Influence	SI1	0.925	0.873	0.876	0.923	0.800
	SI2	0.932				
	SI3	0.822				
Perceived Risk	PR1	0.878	0.871	0.876	0.921	0.795
	PR2	0.915				
	PR3	0.881				
Perceived Entertainment	PE1	0.925	0.925	0.927	0.953	0.870
	PE2	0.944				
	PE3	0.929				
Adoption Behavior	AB1	0.906	0.936	0.936	0.954	0.839
	AB2	0.917				
	AB3	0.920				

	AB4	0.920				
Actual Usage	AU1	0.960	0.915	0.915	0.954	0.839
	AU2	0.960				

Source: Developed for the research

The outer loading of each item on the corresponding construct must be bigger than the loading of the item on other constructs in order to prove discriminant validity utilizing the cross-loadings approach (Chin, 1998). As indicated by table 4.4, in this instance, each item's outer loading on the related construct was higher than the item's loading on other constructs. There are issues with discriminant validity if the HTMT levels are high. According to Hair et al. (2019), a result of 0.90 or less would indicate the presence of discriminant validity. Table 4.5 shows that most of the constructions have met the more conservative cut-off value suggested by Henseler et al. (2015), which is a threshold value of less than 0.85. However, there were two correlations between the constructs with HTMT values of 0.859 and 0.853, which were both greater than 0.85 but less than 0.90. The HTMT threshold value indicated that the value was acceptable.

Table 4.4: Cross Loading Criterion Results

	AB	AU	EE	PE	PEX	PR	SI
AB1	**0.906**	0.682	0.626	0.679	0.722	0.547	0.688
AB2	**0.917**	0.69	0.622	0.687	0.687	0.574	0.71
AB3	**0.92**	0.716	0.592	0.673	0.691	0.547	0.645
AB4	**0.92**	0.718	0.603	0.669	0.713	0.566	0.64
AU1	0.736	**0.96**	0.585	0.639	0.714	0.51	0.647
AU2	0.735	**0.96**	0.61	0.662	0.698	0.541	0.669
EE1	0.55	0.544	**0.847**	0.595	0.658	0.441	0.525
EE2	0.538	0.485	**0.898**	0.611	0.678	0.488	0.604
EE3	0.605	0.572	**0.905**	0.642	0.707	0.467	0.662
EE4	0.587	0.572	**0.874**	0.579	0.681	0.414	0.607
EE5	0.59	0.478	**0.869**	0.618	0.668	0.431	0.637
EE6	0.643	0.626	**0.89**	0.653	0.717	0.449	0.599
PE1	0.661	0.6	0.639	**0.925**	0.735	0.49	0.655

PE2	0.683	0.624	0.652	**0.944**	0.736	0.489	0.687
PE3	0.722	0.668	0.669	**0.929**	0.767	0.501	0.705
PEX1	0.644	0.673	0.677	0.687	**0.872**	0.434	0.628
PEX2	0.653	0.629	0.642	0.666	**0.853**	0.457	0.693
PEX3	0.703	0.65	0.675	0.721	**0.894**	0.52	0.724
PEX4	0.616	0.569	0.645	0.706	**0.879**	0.446	0.628
PEX5	0.617	0.613	0.683	0.682	**0.857**	0.517	0.627
PEX6	0.732	0.683	0.726	0.704	**0.853**	0.515	0.706
PR1	0.552	0.521	0.474	0.523	0.532	**0.878**	0.527
PR2	0.58	0.511	0.456	0.478	0.514	**0.915**	0.449
PR3	0.494	0.423	0.428	0.408	0.435	**0.881**	0.406
SI1	0.666	0.616	0.619	0.678	0.692	0.445	**0.925**
SI2	0.67	0.616	0.627	0.714	0.703	0.497	**0.932**
SI3	0.628	0.606	0.601	0.566	0.675	0.446	**0.822**

Source: Developed for the research

Table 4.5: HTMT Results

	AB	**AU**	**EE**	**PE**	**PEX**	**PR**	**SI**
AB							
AU	0.828						
EE	0.708	0.668					
PE	0.793	0.735	0.749				
PEX	0.814	0.792	0.827	**0.859**			
PR	0.673	0.610	0.561	0.587	0.612		
SI	0.811	0.768	0.759	0.813	**0.853**	0.593	

Source: Developed for the research

4.3 Structural Model Assessment

It is essential to determine the degree of collinearity before assessing the structural model. VIF values between 3 and 5 are typically regarded as acceptable because they are not critical (Hair et al., 2019). Table 4.5 indicates that there are no signs of collinearity concerns. It is because all of the VIF values are between 1.000 to 4.312 and less than the criterion of 5. According to Hair et al. (2019), larger values of the R^2, which range from 0 to 1, suggest greater explanatory power. R^2 values of 0.75, 0.50, and 0.25 are considered significant, moderate, and weak, respectively. The dependent constructs' coefficient of determination (R^2), adoption behavior (AB), and actual usage (AU) are displayed in Table 4.6. The R^2 value and adjusted R^2 value in AB and AU are both acceptable. With an adjusted R^2 value of 0.679 and an R^2 value of 0.687 for the AB construct, these values suggest a moderate impact size. This indicates that 68.7% of the variance in the adoption behavior towards using ChatGPT in the learning process of UTAR students can be explained by the five (5) independent factors (PEX, EE, PR, PE, and SI), with other variables accounting for the remaining 31.3% of the variance. Furthermore, with an adjusted R^2 value of 0.585 and an R^2 value of 0.587, the AU construct showed a moderate impact size. This implied that adoption behavior explained 58.7% of the variance in actual usage of ChatGPT in UTAR students' learning process.

Table 4.6: Structural Model's Construct Assessment Result

	VIF	f2		R-square	R-square adjusted
AB-->AU	1.000	1.421	**AB**	0.687	0.679
EE-->AB	2.758	0.002	**AU**	0.587	0.585
PE-->AB	3.168	0.050			
PEX-->AB	4.312	0.049			
PR-->AB	1.527	0.088			
SI-->AB	2.832	0.062			

Source: Developed for the research

4.4 Hypotheses Testing

In order for the hypotheses to be accepted, t-statistic must be higher than 1.96 (Hair et al., 2019). Furthermore, according to Lohmöeller (1989), p-values less than 0.05 are considered statistically significant, and the path coefficient was greater than 1. Table 4.7 shows that a non-significant path coefficient value of 0.046, t-statistics value of 0.506, and p-value of 0.613 reject a relationship between effort expectancy and adoption behavior (H2). The association between adoption behavior and perceived risk (H4) is thus likewise rejected as indicated by a p-value of 0.059, a path coefficient value of 0.205, and a statistics value of 1.901. Furthermore, a non-significant path coefficient value of 0.222, a t-stat value of 0.805, and a p-value of 0.073 reject the relationship between perceived entertainment and adoption behaviour (H5). With a path coefficient value of 0.256, a t-statistics value of 2.384, and a p-value of 0.018, the relationship between adoption behavior and performance expectancy (H1) is positively correlated and highly significant. Similarly, the path coefficient value of 0.235, t-statistics value of 2.745, and p-value of 0.007 all support the relationship between social influence and adoption behavior (H3), indicating that it has a positive relationship and highly statistically significant. Finally, the relationship between adoption behavior and actual usage (H6) is positive related and highly significant with a path coefficient value of 0.766, t-statistics value of 11.992.

Table 4.7: Hypotheses Testing Result

	Path Coefficient (β)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistic (|O/STDEV|)	P-Values	Interference
H1: PEX-->AB	0.256	0.262	0.107	2.384	0.018	Supported
H2: EE-->AB	0.046	0.048	0.092	0.506	**0.613**	Not Supported
H3: SI-->AB	0.235	0.227	0.085	2.745	0.007	Supported

H4: PR-->AB	0.205	0.198	0.108	1.901	**0.059**	Not Supported
H5: PE-->AB	0.222	0.227	0.123	1.805	**0.073**	Not Supported
H6: AB-->AU	0.766	0.757	0.064	11.992	0.000	Supported

Source: Developed for the research

4.5 Conclusion

This chapter covered descriptive analysis, measurement model evaluation, structural model assessment, and hypothesis testing. In this case, H1, H3, and H6 are supported by the structural model evaluation results.

CHAPTER 5: DISCUSSION & CONCLUSION

5.0 Introduction

This chapter will cover in detail the findings that were demonstrated in Chapter 4, as well as the study's limitations, implications, and recommendations for further research. It will also conclude with a full discussion.

5.1 Discussion of Major Findings

Table 5.1: Summary of Hypothesis Testing Results

Hypothesis	**P-value**	**Result**
H1: There is a significant relationship between performance expectancy and adoption behavior.	0.018	Supported
H2: There is a significant relationship between effort expectancy and adoption behavior.	0.613	Not Supported
H3: There is a significant relationship between social influence and adoption behavior.	0.007	Supported
H4: There is a significant relationship between perceived risk and adoption behavior.	0.059	Not Supported
H5: There is a significant relationship between perceived entertainment and adoption behavior.	0.073	Not Supported
H6: There is a significant relationship between adoption behavior and usage.	0.000	Supported

Source: Developed for the study

H1: There is a significant relationship between performance expectancy (PEX) and adoption behavior (AB).

PEX and AB have a positive relationship, according to Table 5.1. Previous research by Li et al. (2016) and Lin et al. (2022) supports the finding. In this instance, UTAR students might believe that by having quick access to knowledge, conceptual clarification, and help with problem-solving, ChatGPT can improve their learning outcomes. Adoption may be influenced by expectations that the technology would improve academic performance.

H2: There is a significant relationship between effort expectancy (EE) and adoption behavior (AB).

The results indicated that EE has no effect on AB, as shown in Table 5.1. The p-value of 0.613 shows that H2 is not significant in this research. This result went against the findings of Wong et al. (2015)'s earlier study, which claimed that effort expectancy is regularly recognized as a critical factor influencing user adoption behavior. Nevertheless, earlier research has also found a negative correlation between EE and AB with technological innovation, such as the adoption of remote mobile payments (Slade et al. 2015). According to Chong's (2013) findings, EE had no influence on AB's decision to use mobile commerce; this was attributed to AB's comfort level with the devices. The previous study shows why the effect of EE on AB is more important for nonusers who are unfamiliar with remote mobile payment; those who are already familiar with mobile payment are likely to be familiar with the functioning of remote mobile payment. Consequently, given the current study's setting, one explanation for this would be that ChatGPT is a relatively new technology, having only launched in November 2022. As a result, many users still do not know how to use ChatGPT and believe it will be difficult for them to learn.

H3: There is a significant relationship between social influence (SI) and adoption behavior (AB).

Table 5.1 demonstrates that there is a significant relationship between SI and AB. Customers typically install the same applications as a reference group, such as friends, family, or a work colleague, in order to communicate and share knowledge with them. This finding has been confirmed by earlier research conducted by Chua et al. (2018). According to a previous study by Liébana-Cabanillas et al. (2018), users generally behave in a particular way in order to live up to the expectations of their friends, family, and the larger community. In this scenario, when students decide to include a new technology such as ChatGPT into their learning process, social influence may have an impact on their ideas and values, and people respond to social pressure by acting in specific ways.

H4: There is a significant relationship between perceived risk (PR) and adoption behavior (AB).

According to Table 5.1, the results show that PR has no influence on AB, with a p-value of 0.059, which is greater than 0.05. This indicates that H4 in this investigation is not statistically significant. This result opposes the conclusions of Lin et al.'s earlier study from 2022, which found that PR and AB had a negative connection. This indicates that if a person perceives a high level of risk, they will adopt new technology less quickly. Past research has also revealed that PR has no influence on AB, meaning that people would continue to accept new technology even if it poses a risk. The results of perceived risk and trust as unitary factors on adoption behavior were validated by previous research conducted by Chang & Wu (2012). Trust and perceived risk have long been acknowledged in marketing literature as significant determinants of consumer behavior. According to Slade et al. (2015), trust was also discovered to have an indirect impact on behavioral intention to accept remote mobile payments through this relationship. The present study highlights the correlation between perceived risk and confidence in remote mobile payment systems. Therefore, it is crucial to employ advanced security measures and provide assurances about security and privacy. Furthermore, policies that ensure satisfaction are another type of trust-building strategy that could aid in lowering risk perceptions (Lu et al., 2011). As a result, even though ChatGPT may result in information leakage, privacy violations, and misuse of personal information, UTAR students continue to use it in their learning process. It can be as a result of users' great happiness and sense of trust with ChatGPT.

H5: There is a significant relationship between perceived entertainment (PE) and adoption behavior (AB).

According to Table 5.1, the results demonstrate that the PR has no impact on AB, with a p-value of 0.073, which is greater than 0.05. As a result, H5 is not statistically significant in the current study. This result opposes the results of a prior study by Lin et al. (2022), which found that PE had the greatest positive impact on user AB. This could be because the future generation of users of AI-enabled online education products is probably interested in engaging in learning. Past research has also discovered that PE has no effect on how AB is shaped. Al-Abdullatif and Mohammed (2023) claimed that there is no evident relationship between students' adopting behavior towards chatbots and their perception of amusement. Users might not be aware of a chatbot's instructional potential if the overall perception is mostly for pleasure. They might not use or explore its features, which could provide for a more productive learning environment. Thus, in this scenario, it is possible to speculate that UTAR students typically regard ChatGPT as beneficial rather than enjoyable.

H6: There is a significant relationship between adoption behavior (AB) and actual usage (AU).

Table 5.1 demonstrates that there is a positive relationship between AB and AU. The results have been supported by earlier research conducted by Chatterjee and Bhattacharjee (2020), which noted that adoption behavior had a substantial impact on how technology was actually used in higher education and language e-learning programs (Lin et al., 2022). According to the current study, UTAR students who have adopted the practice of using ChatGPT in their learning will actually use ChatGPT during their learning process. As a result, the current study provided more evidence of the adopting behavior's substantial impact on students' actual usage.

5.2 Implications of the Study

This section covers the theoretical implications and managerial implications.

5.2.1 Theoretical Implication

The Unified Theory of Acceptance and Use of Technology (UTAUT) model provided the theoretical foundation for the conceptual framework of the current study. This study aims to investigate the students' adoption behavior with ChatGPT in their learning process and the factors that will impact their adoption behavior (PEX, EE, SI, PE, PR) and further influence the actual usage of ChatGPT. The findings of this study provide more proof that the UTAUT model are applicable when it comes to the acceptability of AI in education. Any research model must be modified to maintain its relevance and appropriateness. Stated differently, the goal is to maintain the model's relevance to the ever-changing environment. The constructs of EE, PR, and PE were found to have no influence on consumers' adoption behavior on ChatGPT during the learning process, according to the results of the current study. Consequently, in the future, researchers can think about substituting these variables with others that might have significant effects on users' adoption of new innovations or technologies.

5.2.2 Managerial Implication

The results of the current study offered a number of managerial implications and recommendations to educators who plan to integrate ChatGPT into their students' learning process. First of all, the survey indicates that students are open to using ChatGPT if it helps them be more productive with their assignments. If users think a technology will improve their performance or help them with their jobs and goals, they are more willing to adopt and use it. Educational institutions ought to create extensive training curricula to encourage a full comprehension of ChatGPT's capabilities. These presentations ought to stress not just ChatGPT's features but also how it might improve academic achievement. By equipping students with the necessary information and abilities to utilize ChatGPT efficiently, educational institutions can positively impact the way people perceive the tool's capabilities. For example, educators can give engaging hands-on workshops in which students actively use ChatGPT under the supervision of instructors. Through this hands-on experience, they will become more proficient and confident in using the tool.

Second, the study found that students are more likely to utilize ChatGPT if most of the individuals around them are doing so as well. By urging early adopters to share their positive experiences with the student, educators may capitalize on the power of peer recommendations and testimonials. In order to generate attractive buzz about ChatGPT, it is imperative to establish a strong presence on social media platforms where students are actively involved. This will facilitate the sharing of user experiences, success stories, and pertinent content. Implementing a student ambassadors' program increases social influence by allowing enthusiastic users to promote the ChatGPT within their peer groups, answering questions, and sharing insights. Social proof increases the trustworthiness and appeal of marketing materials. Examples of this type of proof include displaying the number of students or academic institutions that use ChatGPT.

Lastly, based on this research, there is a positive relationship between adoption behavior and actual usage of ChatGPT adoption among UTAR students. Consequently, educators have an obligation to offer prompt and helpful assistance to students who encounter difficulties. Furthermore, asking student comments on a frequent basis can yield insightful information for enhancements, and monitoring student usage of ChatGPT through analytics facilitates decision-making. Users find the tool more engaging when they may customize it to some extent.

5.3 Limitations and Recommendations

As with any research, there are several limitations to this research. In order to verify a user's actual experience and accomplishment, the researcher should have added a filter question to the Google Form to make sure that every respondent had utilized ChatGPT. This was not done by the researcher in this survey, hence only 195 out of 200 respondents used ChatGPT, affecting the study's accuracy. 5 out of 200 respondents did not use ChatGPT. To guarantee the quality and accuracy of this research, it is advised that future researchers include a filter question in the questionnaire.

Lastly, this study is exclusive for UTAR. It may be replicated in other study. Therefore, it is recommended that future researchers can also consider comparison between private and public university. For example, future researcher can investigate the students at other private universities such as Tarumt, and Sunway and compare with public university like UM, and UTM.

5.4 Conclusion

In summary, this chapter covered discussion, implications, limitations, and recommendations. This research has provided insightful information about the adoption of AI in education among UTAR students in the case pf ChatGPT.

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APPENDICES

Appendix A: Questionnaire

Adoption of AI Techonology in Education Among UTAR Students.

Dear respondents,

Good day everyone! I'm researcher Heng Wei Ni from the Bachelor of International Business (HONS) of Universiti Tunku Abdul Rahman (UTAR).

I am currently conducting a research to find out

Adoption of AI Technology in Education Among UTAR Students.

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 technology with variables covering student's performance expectancy, effort expectancy, social influence, perceived risk, perceived entertainment, adoption behavior, and actual usage towards ChatGPT in students' learning process. 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 performance expectancy, effort expectancy, social influence, perceived risk, perceived entertainment, adoption behavior, and actual usage towards ChatGPT in students' learning process will be asked.

The survey should take approximately 5 to 10 minutes to complete. Thank you for being a part of this research! If you have any questions or concerns about the survey, feel free to contact me.
Yours sincerely,

Heng Wei Ni
012-2800513
wennie130502@1utar.my

* Indicates required question

Demographic

1. Gender *

Mark only one oval.

- Male
- Female

2. Education Level *

Mark only one oval.

- Foundation
- Undergraduate
- Postgraduate (eg. Master and above)

3. Year Semester *

Mark only one oval.

- Year 1
- Year 2
- Year 3
- Year 4

4. Stream *

Mark only one oval.

- Science Stream (eg. Medical studies, Engineering, Computer Science)
- Art Stream (eg. Accounting, Business, Education)

5. Race *

Mark only one oval.

- Malay
- Chinese
- India
- Other: ____________________

6. Have you used ChatGPT in your learning process before? *

Mark only one oval.

- Yes
- No

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)

7. Performance Expectancy *

Mark only one oval per row.

	SD	D	SWD	N	SWA	A	SA
1. Using ChatGPT in my job would enable me to accomplish tasks more quickly.	⬭	⬭	⬭	⬭	⬭	⬭	⬭
2. Using ChatGPT would improve my academic performance.	⬭	⬭	⬭	⬭	⬭	⬭	⬭
3. Using ChatGPT for my job would increase my productivity.	⬭	⬭	⬭	⬭	⬭	⬭	⬭
4. Using ChatGPT would enhance my effectiveness on my job.	⬭	⬭	⬭	⬭	⬭	⬭	⬭
5. Using ChatGPT would make it easier to do my job.	⬭	⬭	⬭	⬭	⬭	⬭	⬭
6. I would find ChatGPT useful in my job.	⬭	⬭	⬭	⬭	⬭	⬭	⬭

8. Effort Expectancy *

Mark only one oval per row.

	SD	D	SWD	N	SWA	A	SA
1. Learning to operate ChatGPT would be easy for me.							
2. I would find it easy to get ChatGPT to do what I want it to do.							
3. My interaction with ChatGPT would be clear and understandable.							
4. I would find ChatGPT to be flexible to interact with.							
5. It would be easy for me to become skillful by using ChatGPT.							
6. I would find ChatGPT easy to use.							

9. Social Influence *

Mark only one oval per row.

	SD	D	SWD	N	SWA	A	SA
1. People who are important to me think that I should use ChatGPT.	⬭	⬭	⬭	⬭	⬭	⬭	⬭
2. People who influence my behavior think that I should use ChatGPT.	⬭	⬭	⬭	⬭	⬭	⬭	⬭
3. Most people surrounding me use ChatGPT.	⬭	⬭	⬭	⬭	⬭	⬭	⬭

10. Perceived Risk *

Mark only one oval per row.

	SD	D	SWD	N	SWA	A	SA
1. I am concerned that using ChatGPT will lead to information leakage, violation and misuse of personal information.	⬭	⬭	⬭	⬭	⬭	⬭	⬭
2. I am concerned about the quality of academic information obtained using ChatGPT.	⬭	⬭	⬭	⬭	⬭	⬭	⬭
3. I am concerned that the academic information obtained through ChatGPT will not meet my expectations and I do not know how to protect my rights.	⬭	⬭	⬭	⬭	⬭	⬭	⬭

11. Perceived Entertainment *

Mark only one oval per row.

	SD	D	SWD	N	SWA	A	SA
1. I find using ChatGPT to be enjoyable.	⬭	⬭	⬭	⬭	⬭	⬭	⬭
2. The actual process of using ChatGPT is pleasant.	⬭	⬭	⬭	⬭	⬭	⬭	⬭
3. I have fun using ChatGPT.	⬭	⬭	⬭	⬭	⬭	⬭	⬭

12. Adoption Behavior *

Mark only one oval per row.

	SD	D	SWD	N	SWA	A	SA
1. I will continue to acquire ChatGPT related information.	⬭	⬭	⬭	⬭	⬭	⬭	⬭
2. I will keep myself updated with the latest ChatGPT applications.	⬭	⬭	⬭	⬭	⬭	⬭	⬭
3. I intend to use ChatGPT to assist with my learning.	⬭	⬭	⬭	⬭	⬭	⬭	⬭
4. I will continue to learn ChatGPT.	⬭	⬭	⬭	⬭	⬭	⬭	⬭

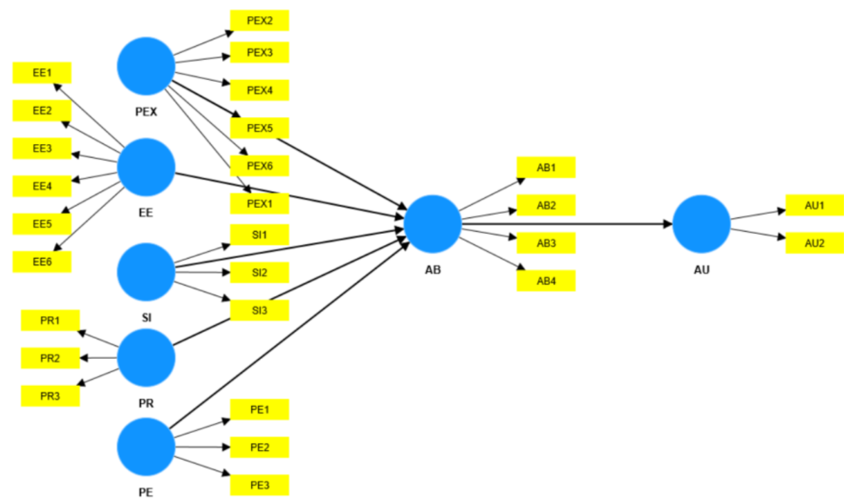
13. Actual Usage *

Mark only one oval per row.

	SD	D	SWD	N	SWA	A	SA
1. I will personally use ChatGPT during learning process.	⬭	⬭	⬭	⬭	⬭	⬭	⬭
2. I will personally use ChatGPT as a reference for learning activities.	⬭	⬭	⬭	⬭	⬭	⬭	⬭

Appendix B: SmartPLS Output

Measurement model



Factor loading

Outer loadings

Matrix List

	AB	AU	EE	PE	PEX	PR	SI
AB1	0.906						
AB2	0.917						
AB3	0.920						
AB4	0.920						
AU1		0.960					
AU2		0.960					
EE1			0.847				
EE2			0.898				
EE3			0.905				
EE4			0.874				
EE5			0.869				
EE6			0.890				
PE1				0.925			
PE2				0.944			
PE3				0.929			
PEX2					0.853		
PEX3					0.894		
PEX4					0.879		
PEX5					0.857		
PEX6					0.853		
PR1						0.878	
PR2						0.915	
PR3						0.881	
SI1							0.925
SI2							0.932
SI3							0.822
PEX1					0.872		

Construct Reliability and Validity

Construct reliability and validity

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
AB	0.936	0.936	0.954	0.839
AU	0.915	0.915	0.959	0.922
EE	0.942	0.944	0.954	0.776
PE	0.925	0.927	0.953	0.870
PEX	0.935	0.937	0.948	0.754
PR	0.871	0.876	0.921	0.795
SI	0.873	0.876	0.923	0.800

Discriminant Validity: Cross Loading Criterion

Discriminant validity

Heterotrait-monotrait ratio (HTMT) - Matrix | Heterotrait-monotrait ratio (HTMT) - List | Fornell-Larcker criterion | Cross loadings

	AB	AU	EE	PE	PEX	PR	SI
AB1	0.906	0.682	0.626	0.679	0.711	0.547	0.688
AB2	0.917	0.690	0.622	0.687	0.687	0.574	0.710
AB3	0.920	0.716	0.592	0.673	0.691	0.547	0.645
AB4	0.920	0.718	0.603	0.669	0.713	0.566	0.640
AU1	0.736	0.960	0.585	0.639	0.714	0.510	0.647
AU2	0.735	0.960	0.610	0.662	0.698	0.541	0.669
EE1	0.550	0.544	0.847	0.595	0.658	0.441	0.525
EE2	0.538	0.485	0.898	0.611	0.678	0.488	0.604
EE3	0.605	0.572	0.905	0.642	0.707	0.467	0.662
EE4	0.587	0.572	0.874	0.579	0.681	0.414	0.607
EE5	0.590	0.478	0.869	0.618	0.668	0.431	0.637
EE6	0.643	0.626	0.890	0.653	0.717	0.449	0.599
PE1	0.661	0.600	0.639	0.925	0.735	0.490	0.655
PE2	0.683	0.624	0.652	0.944	0.736	0.489	0.687
PE3	0.722	0.668	0.669	0.929	0.767	0.501	0.705
PEX2	0.653	0.629	0.642	0.666	0.853	0.457	0.693
PEX3	0.703	0.650	0.675	0.721	0.894	0.520	0.724
PEX4	0.616	0.569	0.645	0.706	0.879	0.446	0.628
PEX5	0.617	0.613	0.683	0.682	0.857	0.517	0.627
PEX6	0.732	0.683	0.726	0.704	0.853	0.515	0.706
PR1	0.552	0.521	0.474	0.523	0.532	0.878	0.527
PR2	0.580	0.511	0.456	0.478	0.514	0.915	0.449
PR3	0.494	0.423	0.428	0.408	0.435	0.881	0.406
SI1	0.666	0.616	0.619	0.678	0.692	0.445	0.925
SI2	0.670	0.616	0.627	0.714	0.703	0.497	0.932
SI3	0.628	0.606	0.601	0.566	0.675	0.446	0.822
PEX1	0.644	0.673	0.677	0.687	0.872	0.434	0.628

Discriminant Validity: HTMT

Discriminant validity

Heterotrait-monotrait ratio (HTMT) - Matrix | Heterotrait-monotrait ratio (HTMT) - List | Fornell-Larcker criterion | Cross loadings

	AB	AU	EE	PE	PEX	PR	SI
AB							
AU	0.828						
EE	0.708	0.668					
PE	0.793	0.735	0.749				
PEX	0.814	0.792	0.827	0.859			
PR	0.673	0.610	0.561	0.587	0.612		
SI	0.811	0.768	0.759	0.813	0.853	0.593	

Structural Model's Construct Assessment

f-square

Matrix | List

	AB	AU	EE	PE	PEX	PR	SI
AB		1.421					
AU							
EE	0.002						
PE	0.050						
PEX	0.049						
PR	0.088						
SI	0.062						

Collinearity statistics (VIF)

Outer model - List | Inner model - Matrix | Inner model - List

	VIF
AB -> AU	1.000
EE -> AB	2.758
PE -> AB	3.168
PEX -> AB	4.312
PR -> AB	1.527
SI -> AB	2.832

Quality criteria

R-square

	R-square	R-square adjusted
AB	0.687	0.679
AU	0.587	0.585

Hypothesis Testing

Path coefficients

Mean, STDEV, T values, p values | Confidence intervals | Confidence intervals bias corrected

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
AB -> AU	0.766	0.757	0.064	11.992	0.000
EE -> AB	0.046	0.048	0.092	0.506	0.613
PE -> AB	0.222	0.227	0.123	1.805	0.073
PEX -> AB	0.256	0.262	0.107	2.384	0.018
PR -> AB	0.205	0.198	0.108	1.901	0.059
SI -> AB	0.235	0.227	0.085	2.745	0.007