FACTORS AFFECTING MALAYSIAN UNIVERSITIES STUDENTS' INTENTION TO USE ARTIFICIAL INTELLIGENCE (AI)

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PREFACE

The Final Year Project is from our intense curiosity about the swift assimilation of artificial intelligence in the field of education. We were motivated to investigate the factors that influencing students' intention to adopt such technology after observing how AI tools have revolutionized the way that learning is conducted.

This study was developed over several months of reading, observing, and engaging in meaningful discussions with educators, students, and technology experts. In addition to broadening our knowledge of the subject, this process has given us important new perspectives on how AI might improve educational opportunities.

In conclusion, we hope that the results of this study will offer educators, policymakers, and students a better understanding of how AI can be successfully incorporated into educational settings, contributing to both academic literature and real-world applications.

ABSTRACT

With its enormous potential to improve academic support, teaching, and learning, artificial intelligence (AI) is being increasingly used in higher education. However, there is still uncertainty over students' willingness to use AI tools, particularly in the Malaysian higher education environment. Previous research on AI in higher education has mostly focused on particular institutional types, such as public or private institutions, without taking into consideration both contexts. This research aims to investigate the factors that impact Malaysian university students' intention to use AI, with a particular emphasis on perceived usefulness, perceived ease of use, social influence, and habit. A structured questionnaire was used in a quantitative study design and given to students at public and private universities in Kuala Lumpur, Selangor, Perak, Penang, and other areas. Moreover, 384 valid responses have been collected via non-probability sampling. According to the results, students' intention to use AI is significantly positively impacted by perceived ease of use and habit, but not by perceived usefulness or social influence. These findings provide insightful information that helps educational institutions and AI developers better customize AI-related projects that seek to improve student engagement and promote the successful integration of cutting-edge technologies in higher education.

Keywords: artificial intelligence, student intention, perceived usefulness, perceived ease of use, social influence, habit, public university, private universities

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List of Abbreviations

AI	Artificial Intelligence
SI	Student intention to use AI
PEU	Perceived Ease of Use
PU	Perceived Usefulness
SoI	Social Influence
HB	Habit
IV	Independent Variables
DV	Dependent Variables
TAM	Technology Acceptance Model
UTAUT	Unified Theory of Acceptance and Use of Technology
UTAUT2	Unified Theory of Acceptance and Use of Technology 2
TRA	Theory of Reasoned Action
TPB	Theory of Planned Behaviour
CA	Cronbach's Alpha
CR	Composite Reliability
AVE	Average Variance Extracted
VIF	Variance Inflation Factor
ML	Machine Learning
DL	Deep Learning
NLP	Natural Language Processing
CAs	Conversational Agents

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CHAPTER 1: RESEARCH OVERVIEW

1.0 Introduction

This chapter will provide an outline of research background, problem statement, research questions, research objectives, hypothesis, and importance of the study.

1.1 Research Background

In our daily life, the rapidly developing field of AI has affected us in every aspect (Chai et al., 2021). Through AI, a computer system or machine may simulate and do tasks that frequently need intelligence from humans, such as acquiring knowledge, solving problems, and logical thinking (Morandín-Ahuerma, 2022). Applications such as virtual assistants, automated systems, and intelligent learning tools are supported by AI like robots, ML, DL (Soori et al., 2023), and NLP (Mah et al., 2022). CAs, such as Google Assistant, Siri, and AI chatbots, are to assist users with tasks including communication, data processing, and learning (Gupta et al., 2020; Weber & Ludwig, 2020). In education, the use of AI greatly influences various areas, such as enhancing efficacy and efficiency in educational administration, global learning, personalized and customized learning experiences, and the development of smarter content (Timms, 2016).

AI use has spread over several industries, profoundly influencing fields including healthcare (Saini & Kumar, 2024), finance (Cao, 2021), manufacturing (Tran, 2021), and education (Harry, 2023). In the healthcare industry, artificial intelligence (AI) enhances diagnoses, anticipates patient requirements for proactive care, personalizes treatments, and streamlines administration to reduce expenses and maximize resources. (Saini & Kumar, 2024). In the finance industry, Smart banking, insurance, risk assessment, algorithmic trading, and fraud detection can all be made easier with Artificial Intelligence for Data-driven Solutions (AIDS) (Cao, 2021). In the manufacturing industry, Industry 4.0 propels Smart industrial by combining Industrial Internet of Things (IIoT), AI, and Big Data, allowing for quality optimization, cost savings, and predictive maintenance. IIoT sensors gather information, and artificial intelligence (AI) promotes smart product creation, reduces waste, and increases efficiency (Tran, 2021). In the education sector, AI improves education by using machine learning and NLP to increase efficiency, improve engagement, and personalize learning. In the realm of AI, the objective of Computers can now understand, interpret, and produce human language due to NLP. NLP is used to develop conversational AI systems that can offer learners instruction, guidance, and feedback based on natural language regarding personalized understanding (Katiyar et al., 2024). In addition to improving student outcomes and saving teachers time, it makes intelligent tutoring, automated grading, and enhanced feedback possible (Harry, 2023). AI-powered customization could improve learning outcomes, boost motivation and engagement, boost efficiency, and advance educational equity by customizing education to every student's unique needs. (Katiyar et al., 2024). Malaysian universities have incorporated artificial intelligence (AI) like QuillBot, ChatGPT, and Grammarly into the academic environment.

With the advent of ChatGPT and other AI technologies, several industries have undergone radical change, most notably education. Five days after its launch, ChatGPT has accumulated over a million members, positioning itself as a significant competitor in the tech and online sectors (Bhandari, 2023). Earlier iterations of chatbots used textual analysis and crude pattern matching, whereas more recent models are knowledge-based (Hussain et al., 2019, as cited in Haindl & Weinberger, 2024). According to studies, chatbots have been used in both official and informal education for a long time. As part of their applications, they do administrative tasks, enhance student engagement, aid the learning process, and evaluate students' progress (Haindl & Weinberger, 2024).

According to a global survey of students conducted in the middle of 2024, 86% of them were utilizing AI tools for their studies. Almost one-fourth of them used it daily (Statista, 2024). This demonstrates how AI is increasingly being implemented in academic purposes. In order to enhance student performance, the learning environment, and institutional efficiency, higher education institutions must adopt artificial intelligence (Mohammed et al., 2023, as cited in Osman et al., 2024). AI-driven systems like Deepseek and ChatGPT, for instance, simplify difficult research assignments and offer advanced features that let students produce thorough summaries, spot important trends in scholarly literature, and do advanced critical analysis (Cui, 2025). Additionally, AI is used in extracurricular activities such as hackathons, which allow students to explore AI applications and combine theory with real-world problem-solving (Sajja et al., 2024). Keiper (2023) also supported this claim, showing how AI such as ChatGPT being used in event management courses to fasten the planning work. This shows that AI can promote both academic and practical learning by making time-consuming tasks more efficient for both students and professors.

Applications of AI in education provide advantages, but they also present ethical and societal challenges (Akgun & Greenhow, 2021). Positively, by automating administrative and grading activities, AI improves learning efficiency, facilitates tailored education, allows for real-time feedback, and lessens the workload of educators (Harry, 2023). Moreover, computational AI-based systems make the same choices while interacting with pupils regarding their motivational style, problems, abilities, and shortcomings as human tutors. These technologies enable information to be customized to each student's needs and ability level by providing them with flexible and adaptive feedback, which boosts engagement and helps a range of learners (Woolf et al., 2013). Besides that, customers frequently accept the outputs of AI dialogue systems—AI hallucinations—without evaluation because they are unduly dependent on them (Gao et al., 2023). Additionally, bias is a problem that can be incorporated into AI systems' algorithms. Students may experience unfair or discriminating results because of this. In order to create and apply AI in an ethically and responsibly responsible manner, it is imperative that algorithms be transparent and accountable (Lydia et al., 2023). The unthinking acceptance of AI-generated information also made worse by cognitive biases, that arise when decisions deviate from logic, as well as heuristics or mental shortcuts

(Gao et al., 2023). In addition, data privacy, ethics, potential biases, and the digital divide are among the problems (Ray & Deb Prasad Ray, 2024). Due to AI systems need access to vast volumes of student data, questions are raised regarding who can access this data and how it will be used. Therefore, it's critical to set precise rules and regulations for the gathering, utilizing, and disseminating of student data (Lydia et al., 2023).

Although AI adoption in education has gained significant attention, majority of the existing studies are focusing on other industries such as manufacturing, healthcare, and finance, with limited research on higher education. While the use of AI has grown quickly overall, compared to other industries, higher education-specific research is still somewhat limited and dispersed (Bond et al., 2024). Besides, studies that are now available on AI in higher education frequently concentrate on particular university types, such as public or private universities, without considering both settings. For instance, the research aim is to investigate potential applications of AI and modifications for the learning element by educators and policymakers (Helmiatin et al., 2024). Therefore, both public and private universities in Malaysia will be included in our study, which will concentrate on the variables influencing students' intentions to use AI. Factors that we concerned about are PEU (extent to which people believe AI technology are simple to use), PU (extent to which people think AI will improve their education or learning), SoI (extent to the lecturers and classmates influenced the decision to employ AI), and HB (extent to that routine or repeated behavior determine the usage of AI). Understanding these elements is crucial. Despite these benefits, many students are still unaware of AI's potential or are reluctant to use it due to concerns regarding dependability, data privacy, and restricted access (Handoko et al., 2024). Moreover, AI in education is revolutionary shift in pedagogical approaches which has the potential to transform learning results and engagement among students (Namjoo et al., 2023). Through this study, the main elements influencing students' intention to use AI are intended to be discovered, and appropriate regulations to avoid AI misuse are intended to be developed for Malaysian educational institutions.

1.2 Problem Statement

The background of AI is far longer than most people realize, with roots in ancient Greek philosophy and science (Collins et al., 2021). AI is revolutionizing several industries, like learning, by providing intelligent technologies that enhance decision-making, automate procedures, and promote education (Zawacki-Richter et al., 2019). For example, ChatGPT, Grammarly, and Quill Bot are examples of AI technologies due to that have quickly changed how students approach learning. This is because of AI's ability to provide students with immediate answers, automate whitemailing aid, and solve problems. Therefore, it is increasing accessibility to education. Individuals as well as groups define AI as a system that has the capacity to gain knowledge, explain, comprehend, think, adapt, and solve problems (Gbadegeshin et al., 2021).

Besides, Malaysian educational institutions have begun incorporating AI-related courses and resources into their curricula in recognition of the technology's significance. Beginning in 2027, elementary school students would be taught the fundamentals of AI in the classroom (Harun & Sallehuddin, 2024). They assert that for Malaysia to remain comparable in the global market of the information age, the ministry is committed to creating a workforce with knowledge and experience in AI. Therefore, the necessity for specialized AI deployment tactics within educational institutions was highlighted by a study that looked at AI acceptability in university settings and found that subgroup variations had a substantial impact on adoption trends (Acosta-Enriquez et al., 2024). A separate investigation that examined graduates in Malaysia discovered some factors that contributed to the adoption of AI, indicating that people are starting to realize how AI could enhance educational settings (Razak et al., 2024).

Furthermore, Students whose use adaptable instructional materials perform better on tests and have higher retention rates, according to findings released in the Journal of Learning Analytics (Das et al., 2024). Thus, there are still a lot of promises for improving teaching and learning processes with AI-driven personalized learning. This is due to when examining the current situation of AI absorption in education, numerous things must be considered, such as the rate of adoption and the types of AI technologies being employed, the challenges, and the potential benefits. So, universities are gradually integrating AI into their curricula as they employ it for educational analysis, virtual tutoring, and personalized learning (Li and Zhou, 2020). The promise of AI to enhance educational results and instructional effectiveness is driving adoption (Malhotra et al., 2023; Mittal & Jora, 2023).

However, rather than using AI tools to advance their expertise and abilities, many learners utilize them as a shortcut. AI lacks the advanced awareness and inventiveness associated with cognitive talents, despite its quick processing and analysis of data (Vieriu & Petrea, 2025). A recent survey by the Digital Education Council, a global organization of universities and companies committed to improving education, found that the majority of students (86%) reported utilizing AI in their course work. Additionally, university and college student globally use AI frequently like 54% of respondents said they use it every day or every week, and 24% said they use it every day (Kelly, 2024) While in Malaysia, 69.44% of students agreed that all students should get instruction in AI, most of students (71%) believed that it would help their future jobs. About 44.5% of students thought they were graduating with the abilities needed to work with AI (Tung & Dong, 2023). This stresses the importance of an extensive plan for integrating AI, assuring that it enhances rather than substitutes personal connection and the acquisition of analytical skills (Wu, 2023). For example, the chance of students misused AI technologies in ways that are illegal or prohibited, like completing assignments that use AI-generated content without giving due credit, is increased by Qadir (2023).

Furthermore, there is still variation in how university students use and interact with AI technologies. Several learners exhibit reluctance or an insufficient desire to use AI in their college coursework and future employment due to a variety of factors that contribute, such as perceived utility, ease of implementation, mindset toward AI, social impact, and perceived dangers. Hence, AI illusions, algorithm prejudices, plagiarism, privacy problems, and lack of transparency were among the few research that showed AI conversation systems to have these issues (Zhai et al., 2024). This is due to the creation of misleading or false data, which is a hallmark of AI illusions in AI conversation systems (Hatem et al., 2023). Besides, some research explains that when AI conversation systems produce answers that seem logical and reliable but are deceptive or scientifically inaccurate, this is referred to as an AI illusion. In addition, people have become unduly reliant on AI conversations systems and frequently accept their generated outputs also known as AI hallucinations without examination (Gao et al., 2023). This is due to when the system gives responses that sound imposing but might be erroneous or deceptive. This overreliance can result in less critical thinking, misplaced faith in the AI's skills, and disinformation. Hence, higher education organizations must specify the function and scope of AI in student education (Holmes & Tuomi, 2022).

The use of AI has been thoroughly examined in a number of areas, such as manufacturing (Tran, 2021), healthcare (Saini & Kumar, 2024), and finance (Weber et al., 2023). These studies demonstrate how AI improves technology, decision-making, and efficiency in operations across a range of professional domains. Nevertheless, there is still a dearth of study on the use of AI in higher education, especially when it comes to the variables affecting students' behavioral intentions towards AI adoption. While investigation into the use of AI for learning has been performed, much of it has focused on the applications of AI rather than students' ability to interact with these tools.

Morover, instead of comparing the two, current research on the application of AI in higher education frequently focuses on specific institutional types, such as public or private institutions. Examining the variations in AI adoption among these institutional contexts in Malaysia is obviously insufficient. For example, in Indonesia's public universities, they are examined AI adoption, and they found out that educators and policymakers use the AI Tools to enhance the learning and other activities since it is very convenient and affordable, but they also facing the risk of using AI and facility condition (Helmiatin et al., 2024). In the meanwhile, studies examine how artificial intelligence (AI) may improve instruction in private sector postsecondary education from a global standpoint (Bing et al., 2024). These studies fail to consider how students' opinions towards the adoption of AI are influenced by variations in financing arrangements, institutional agendas, and technological facilities.

In addition, providing targeted support, identifying achievement gaps, and customizing learning paths for each student are some of the main goals of implementing AI (Surbakti, 2023). Also, AI technology can help students with impairments by providing helpful tools that encourage inclusion and equal educational chances (Hollingsworth, 2024). Moreover, AI technology can support educators with administrative duties like as marking and evaluation, lowering instructors' demands and allowing them to concentrate on enhancing their teaching (Murray, 2025). Therefore, AI technology not only help the student to enhance their academic but also improve the educator teaching quality.

Furthermore, most of the research that has already been done has concentrated on the national adoption of AI at universities, ignoring regional variations. Four different academic hotspots with varying institutional, technical, and economic environments are Kuala Lumpur, Selangor, Perak, and Penang. Students' job goals are influenced by Kuala Lumpur's significant exposure to AI-driven sectors as the capital. While Penang, renowned for its technology-driven economy, provides unique insights on AI engagement within industrially linked educational institutions, Perak boasts a mix of well-established universities and expanding AI projects. Besides, Selangor have many respected universities, and variety of student population which as Malaysia's academic and economic hub. Therefore, examining these four sites, it can provide comprehensive to understand of AI adoption in Malaysia's diverse technical and educational ecological systems.

In our research, we will use TAM to investigate PEU and PU. Besides, UTAUT examine SoI. While UTAUT2 will examine the HB to investigate university student intention to use AI in Malaysia. Firstly, TAM is utilized for studies to investigate the acceptability of new digital technology and digital services (Davis, 1989). While UTAUT theory identifies four primary factors which are expectations for performance, expectations for effort, social influence, and conducive environments all have an immediate impact on student intentions. Venkatesh et al. (2016) expanded UTAUT 2 to incorporate three more structures which are price value, habit, and hedonic incentive. Therefore, these aspects reflect students’ enjoyment, perceived value, and instinctive behavior when utilizing technology. In short, this research tries to make the distinction by including key components from TAM, UTAUT, and UTAUT2, with an emphasis on PU, PEU, SoI, and HB to create a more complete model.

Besides, the research looks at the elements that impact Malaysian university students’ interest in using artificial intelligence which including PU, PEU, SoI, and HB. This is due to previous studies having shown contradictory results which are their intention to use AI was favorably and significantly impacted by PEU (Hamadneh, 2024; Wu et al., 2024). However, Bakhadirov et al. (2024) claim that PEU and intention to use AI are not significantly related.

Furthermore, the study's findings indicate that PU positively affects people's willingness to adopt AI (Wang et al., 2023; Jeong et al., 2024). However, Wu et al. (2024) claims that behavioral desire to employ AI is not significantly influenced by PU.

Moreover, the desire of learners to adopt AI is significantly impacted by SoI (Changalima et al., 2024; C et al., 2024). Yet, the results run counter to previous studies that found no significant impact of SoI on behavioral intention (Zamrin, 2023).

In addition, HB is another aspect that influences the intention to use AI. C et al. (2024) stated that HB is the key element that favorably influences students' intention to use ChatGPT and other AI. Additionally, Sadiq et al. (2025) and Strzelecki (2023) also demonstrate the strong correlation between behavioral purpose and HB. However, HB has no impact on intended behavior (Zhu et al., 2024).

In conclusion, this study demonstrates both significant and non-significant effects on the variables influencing the goal of Malaysian university students to utilize AI. Therefore, there is a need for more study to fully understand how SI to use AI is influenced by PU, PEU, SoI, and HB. In short, the characteristics impacting Malaysian university students' ability to use AI contrast the present research.

1.3 Research Objectives

1.3.1 General Objectives

The objective is to examine the factors affecting Malaysian university students’ intention to use AI.

1.3.2 Specific Objectives

1. To determine whether Malaysian university students’ intention to use AI will be significantly impacted by PEU.
2. To determine whether Malaysian university students’ intention to use AI will be significantly impacted by PU.
3. To determine whether Malaysian university students’ intention to use AI will be significantly impacted by SoI.
4. To determine whether Malaysian university students’ intention to use AI will be significantly impacted by HB.

1.4 Research Question

1.4.1 General Question

1. What factors affect the Malaysian university students’ intention to use AI?
2. What is the level of intensity of Malaysian university student to use AI?

1.4.2 Specific Question

1. Is there a significant impact of PEU on Malaysian university students' intention to use AI?
2. Is there a significant impact of PU on Malaysian university students' intention to use AI?
3. Is there a significant impact of SoI on Malaysian university students' intention to use AI?
4. Is there a significant impact of HB on Malaysian university students' intention to use AI?

1.5 Hypothesis of Study

H1 : There is a significant relationship between PEU and Malaysian University students' intention to use AI.

H2 : There is a significant relationship between PU and Malaysian University students' intention to use AI.

H3 : There is a significant relationship between SoI and Malaysian University students' intention to use AI.

H4 : There is a significant relationship between HB and Malaysian University students' intention to use AI.

1.6 Significance of Study

AI has developed rapidly. It has created both possibilities and difficulties in the education sector. This study is significant because it focuses on the factors that may affect the student intention to use AI. The findings are expected to provide meaningful contributions in four key areas:

1. Student-Centric Insight

This study will greatly benefit students because it explores how these four factors (PEU, PU, SoI, HB) affect their intention to use AI tools, helping them understand how AI can improve their learning experience. Students can use AI tools more effectively by understanding their potential benefits (e.g., time saving, personalized learning, and improved academic performance) as well as their drawbacks (e.g., over-reliance, reduced critical thinking skills, academic misconduct, and ethical problems associated with AI-generated content). Students can make more responsible and informed decisions about using AI after taking all these considerations into account. This can also help them to be consistent with the goals of academic integrity and lifelong learning.

2. Institutional Benefit

This research can also benefit universities. Universities can implement some initiatives (e.g. AI literacy programs, establish ethical guidelines, and implement policies) that support the use of AI after they have a better understanding of students' intentions towards AI tools adoption. Moreover, this research can help universities update academic policies, assessment methods, and teaching practices to adapt to technological changes. As a result, universities can create inclusive learning environments that utilise AI. In addition, the learning environment can also be created to continue cultivating students' critical thinking, problem-solving, and creativity.

3. Policy and Regulatory Guidance

Moreover, this study can also benefit policymakers (e.g. Ministry of Higher Education- MOHE). Policymakers can use the findings as a reference to develop a national framework or policies to regulate the use of AI in higher education. This can help to ensure that higher education institutions using AI more responsibly and ethically. For example, policymakers can use the findings to develop ethical codes, practice standards, and policy documents that can solve the key issues like data privacy, accountability, and transparency.

4. Contribution to Future Research

Last but not least, this study can also benefit future researchers who are interested in this area. This study also can serve as a reference for future researchers because it provides insights and evidence that may be useful for them. Besides, Researchers can use these findings to further explore related areas (e.g., actual user behaviour, and differences between different demographic groups or academic programmes).

1.7 Define Key Term

Each of the variables that will be utilized in the thesis is defined as follows:

1. Student Intention (SI)

The self-directed dedication of an individual to act in a particular manner is known as intention (Boydell & Galavotti, 2022). The likelihood of someone adopting AI apps can be inferred from their behavioral intention (Konstantinos Lavidas et al., 2024). The three fundamental dimensions of AI tools are frequency of usage, effort to use them consistently, and intention to continue using them. Students' motivation, persistence, and consistency are mirrored in these characteristics when they include AI tools into their learning routines.

2. Perceived Ease of Use (PEU)

A person's or the company's belief that a system can relieve them of an obligation is known as PEU. (Wicaksono & Maharani, 2020). In short, this is the platform that is straightforward and easy to navigate increases the likelihood of user engagement, minimising frustration and resistance.

3. Perceived Usefulness (PU)

Perceived Usefulness (PU) is defined as a conviction of an individual or organisation that a system can assist them in their task (Davis, 1989). People are more inclined to accept a system if they think it would boost productivity.

4. Social Influence (SoI)

Venkatesh et al. (2003) defined social influence as the extent to which an individual believes that important others think he or she should use a new system.

5. Habit (HB)

Habit is defined as the degree to which individuals automatically execute their behaviours because of repeated use and prior learning (Limayem, Hirt & Cheung, 2007). In UTAUT 2, it is defined as behavior that happens automatically due to prior experiences (Venkatesh, Thong, & Xu, 2012).

1.8 Chapter Layout

This study examines the impact of factors on Malaysian students' intention to use AI. An introduction, problem statements, aims, questions, hypothesis, and significance are provided in Chapter 1, and the literature on all the variables are reviewed in Chapter 2. Furthermore, Chapter 3 discusses design of research, methods to collect data, sampling design, and proposed analysis tools.

1.9 Chapter Summary

This chapter gives a thorough overview of the research's background and problem statement, focusing on the four factors that affect Malaysian students’ intention to use AI. It also outlines the research's objectives, hypotheses, and significance. A thorough literature review will be presented in the upcoming chapter.

CHAPTER 2: LITERATURE REVIEW

2.0 Introduction

The underlying theories are covered in this chapter, along with definitions for DV and IVs. It aims to generate the hypothesis and demonstrate the theoretical structure that discusses the correlation among various variables.

2.1 Underlying Theories

Since its formation, numerous studies have used the **TAM** as a framework for study in a variety of contexts (Ursavaş, 2012). Fred Davis first developed the TAM in 1986 while pursuing his doctorate. Originally intended to anticipate and explain technology usage behavior, the TAM was based on the more generalized TRA. TAM was developed by combining concepts from organizational behaviour with technological features to determine the elements that affect a user's decision to accept or reject a technology (Davis et al., 1989; Davis, 1989). This research is predicated on the testers' opinions of the system's usefulness and simplicity to use, as well as how these two crucial elements affect their behavioural intention for using it (Baroni et al., 2022). Based on the model, when students think AI is helpful—that is, enhances their performance or learning—their propensity to employ it increases. Furthermore, if AI systems are easy to use, their behavioural aim is reinforced, and their PEU is increased. In this research, PEU refers to students' perceptions of how simple to use AI programs like Grammarly and ChatGPT are, while PU refers to students' belief that these tools can improve their academic performance. According to the TAM, if they believe it is simple to use and that doing so will result in positive outcomes or significant advantages, thus, people are more inclined to use an information system (Harryanto et al., 2019).

TAM provides direct support for two of the study's variables, PU and PEU, as measures of university students' intention to adopt AI.

Venkatesh et al. created the **UTAUT** in 2003 to integrate and expand upon eight previous models of technology adoption, like TAM, TRA, TPB and others. To explain user intention and usage behavior, the theory proposed four main constructs: social impact, performance expectancy, facilitating factor, and effort expectancy (Venkatesh et al., 2003). Social influence is very important to our study. Social influence refers to how pupils interpret the views of influential people, such as teachers and fellow students, about application of AI in the context of education. If individuals believe that significant others in their lives value or support the use of AI, they are more likely to plan to employ it.

Habit is considered a useful construct in **UTAUT2** because it explains prolonged and recurrent usage behaviour, which is particularly relevant to students' intention to use AI. UTAUT 2 was introduced to enhance the UTAUT model's explanatory power by including additional elements. For understanding technology adoption in various circumstances, the UTAUT 2 model is a helpful tool (Venkatesh et al., 2016). Three new UTAUT constructs and moderators which are Habit, Hedonic Motivation, and Price Value were added to better capture consumer behaviour, while the original constructs and moderators were retained (Venkatesh et al., 2012). Alternatively, habits explain how frequently students act without thinking about it. If students become accustomed to utilizing AI tools (for example, for writing, studying, or coding), they are more likely to plan to continue using them.

TAM, UTAUT, and UTAUT2 will combine to provide a strong theoretical framework for understanding and predicting user acceptance and usage of technology in both business and consumer contexts. TAM places more emphasis on PU and PEU, UTAUT considers SoI, and UTAUT2 adds HB as a factor that affects students' intention to use AI. By combining these theories, this study investigates how students' beliefs, social contexts, and usage patterns affect their intentions to use AI in academic settings.

2.2 Review of the Literature

2.2.1 Student Intention to use AI (SI)

Intention is self-directed dedication of an individual to behave in a specific way (Boydell & Galavotti, 2022). The likelihood that a person will use AI applications is shown by their behavioural intention (Konstantinos Lavidas et al., 2024). Students' intention to adopt AI tools in the learning environment shows that they are prepared and committed to continuing to use these resources for both academic and extracurricular purposes. A variety of technological and psychological factors, such as PU, PEU, SoI and HB, impact behavioural intention, a powerful indicator of real usage behaviour, according to TAM, UTAUT, and UTAUT 2 (Davis, 1985; Venkatesh et al., 2012).

Three dimensions that can be used to understand the intention to use AI tools which are the goal of continuing to use AI tools in their academic and extracurricular activities, the effort to consistently use AI tools, and the intention to frequently use AI tools. These dimensions demonstrate the degree to which people use technology regularly and persistently. As digital technologies are increasingly incorporated into learning environments, students' regular use of AI tools is crucial to maximizing their educational benefits. Furthermore, students' positive opinions significantly influence their long-term intention to employ AI technologies, especially on their practicality and simple to use. According to the TAM, students are more likely to embrace and keep using AI when students believe AI technologies are helpful and simple to use (Song & Song, 2023). Additionally, increasing knowledge of AI's advantages may encourage more people to use and incorporate the technology into higher education practices (Yusoff et al., 2023).

This study conceptualizes student intention to use as a multidimensional construct that includes the plan, regularity, and frequency of usage to assess the likelihood of future engagement with AI technologies in learning and extracurricular settings.

2.2.2 Perceived Ease of Use (PEU)

PEU is defined as a level at which an individual believes that using any technology would be effortless (Davis, 1989, as cited in He et al., 2018). AI can reduce the learning curve and cognitive loas associated with its use. Students are more likely to use the AI tool because it is simple to use. This is because it can express the degree to which people think utilizing technology would involve little work, intricacy, or mental strain. For instance, AI is easy to learn, easy to acquire skills, adaptable, and easy to retain (Geddam et al., 2024).

Additionally, more research was conducted on the causes of PEU. A framework outlining variables that influence PEU, such as objective accessibility and self-confidence in the computer (Venkatesh and Davis, 1996). In short, students who have greater faith in their knowledge of technology are more inclined to perceive AI solutions as user-friendly, hence it can affect their decision to utilize AI tools. Besides, TAM which was created by Davis (1989), came up with the idea of PEU. This is due to PEU can affect most people's intention to utilize AI technology which is two most important factors. Numerous users believe that an app will improve their work performance, and the easier to use, the more guests will use it (De Camargo Fiorini et al., 2018).

Moreover, current research has shown the importance that PEU is in affecting students' intentions to adopt AI technologies. PEU has a favorable effect on students' intention to utilize AI technologies, with attitudes and self-confidence serving as mediating variables (Osman et al., 2024). Therefore, students' confidence and favorable perspective against AI tools can be increased when they believe they are easy to use, which can increase the possibility that they will be adopted.

However, even have many previous studies have shown that how PEU influence AI usage intention among the university student, but not much has been done on how PEU influence general e-learning tools especially in Malaysia. For example, A study of undergraduates in Kedah found that students often utilised AI chatbots and academic assistance tools because they thought they were very valuable and easy to use. However, adoption was still limited since students had trouble with their technological abilities (Mustaffa, 2025). Hence, it shows the important of PEU in Malaysia context.

In summary, there are real-world implications for integrating AI in education if we comprehend the relationship between PEU and behavioral intention (Alshammari & Babu, 2025). Hence, for the purpose of encouraging the use of AI tools, we recommend that educational institutions invest in user-friendly design as well as sufficient guidance and instruction to enable students to fully benefit from these tools. So, they can increase students' intention, which will increase the possibility that they will continue to use and integrate AI into their education.

2.2.3 Perceived Usefulness (PU)

PU is the degree to which an individual believes that applying a given system may improve their efficiency at workplace (Davis, 1989, as cited in He et al., 2018). This is because it represents users' perceptions that using the technology would increase their performance, efficiency, or production in accomplishing their objectives. For example, Work Faster, Job Achievement, Beneficial, and Efficient (Geddam et al., 2024).

Besides, this idea is fundamental to the TAM, which holds that the main factors influencing user adoption and utilization behavior are perceived usefulness (Rubiyanti et al., 2023). To be able to assess its perceived usefulness, researchers created a new tool, highlighting the necessity of trustworthy and verified metrics in managerial information systems (Larcker & Lessig, 1980). For instance, in e-learning platforms, perceived usefulness is enhanced by providing service performance, and technological assistance, platform effectiveness, and data integrity are important predictors of perceived usefulness (Alsabawy et al., 2016).

Furthermore, an individual or organisation has no desire to adopt an arrangement if they do not think it can assist them in their job (Aditya & Wardhana, 2016). This is because PU could indicate an individual's intellectual assessment of the advantages of utilizing a certain technology. Consequently, students believe that

AI applications like ChatGPT, autonomous tutoring systems, and automated evaluation systems can improve their understanding of the course material, help them finish assignments more quickly, and help them get higher scores. As a result, they are more likely to accept and keep adopting this kind of technology.

Moreover, artificial intelligence for Education can boost learning effectiveness and productivity, which encourages ongoing adoption (Musyaffi et al., 2024). Plus, PU has a crucial role in persuading someone to adopt technologies (Liébana-Cabanillas et al., 2020). To aid students in becoming their own assistants, AI suppliers had to give priority to effectiveness. Therefore, there is a chance to boost high-tech acceptance once students think that technology may boost performance at work.

In conclusion, increasing the perceived value of AI technologies is essential to their effective integration in learning environments. The observable advantages of AI apps can raise students' academic achievement and give them the necessary assistance to finish their coursework or extracurricular activities. As a result, educators may promote favourable opinions and motivate students to incorporate AI into their education.

2.2.4 Social Influence (SoI)

Social Influence is defined as how the opinions, decisions, or actions of a person's are influenced by people who are around them (Khatimah, Susanto & Abdullah, 2019). This influence can arise from people they are close to (e.g. friends, family, or teachers) or can arise from the community (e.g. social media or classmates) (Telzer et al., 2017). Venkatesh et al. (2003) defined social influence as the level to which an individual believes that people who are close to them think they should adopt a certain technology. This means that if people find that people around them suggest using the new technology, they are more willing to use it. The impact of social influence is strong when people are unsure or unfamiliar with the new technology.

Social influence can form in two ways, which are direct and indirect ways. Direct social influence occurs when someone explicitly advises or encourages another to use a certain technology. For instance, students will be encouraged to use AI tools (e.g. Grammarly) by their lecturer to assist in completing their assignment. However, indirect social influence may occur when the person observes the behavior of others and feels that he or she should follow them. For instance, even if no one explicitly instructs them to use that AI tool, students may still do so if they observe many of their friends using it to complete an assignment. Sometimes they do so because they trust the judgement of those around them (Liu et al., 2015).

There are several important behavioral theories that include social influence as one of the elements. For example, in the UTAUT, one of the main predictors for behavioral intention is social influence (Venkatesh et al., 2003). In addition, it has similarities with concepts such as subjective norms in TRA and TPB (Fishbein & Ajzen, 1975; Ajzen, 1991). Although different models use different terms, they convey the same concepts.

Much research has supported this concept, especially in the academic sector. Changalima et al. (2024) have found that lecturers and peers frequently encourage students to employ AI technologies in their studies.. In addition, C et al. (2024) observed that the intention of students to use AI tools was significantly influenced by recommendations from friends and instructors. These findings suggest that students’ confidence and motivation to use new technologies will increase if they receive support from their important people. This is because people's decisions to use new technology are significantly impacted by their friends and family (Cokins et al., 2020).

Although both TRA and TPB embrace the significance of subjective norms, they are limited in their understanding of social influence. They only consider the extent to which social norms influence an individual's behavior. However, UTAUT has a wider and technology-focused understanding of social influence. Since students like to share their experience and follow the latest trends, UTAUT is better suited to study the usage intention of digital tools like AI in university settings.

In the Malaysian context, university students live in a highly social environment where peer actions and expectations of student performance tend to shape their decisions more frequently. Since AI tools are gaining popularity among academic and extracurricular environments, social influence will become a strong factor that affects student intention towards adopting AI tools. Therefore, social influence is one of the main factors in this study that predicts students' intention to use AI tools.

2.2.5 Habit (HB)

Habits are the extent to which people tend to carry out actions automatically because of frequent engagement and past learning (Limayem, Hirt & Cheung, 2007; Gwebu et al., 2014). When people perform the same activity repeatedly until it becomes part of their daily routine, they cultivate a habit. When it comes to using technology, habits are formed when people use a product or platform so frequently that they don't have to hesitate or think twice about using it every time. For example, students who often use an AI tool to check grammar or summarize reading may develop a natural habit of doing it as part of their academic workflow.

Habits are cultivated via familiarity and repetition (Arielli, 2024). People are more inclined to repeat their behavior when it becomes part of their daily routine, and they feel comfortable. In a university context, students are often using AI tools for their academic or extracurricular activities. For example, they may use AI tools to do their assignment or use AI tools to plan events or generate ideas for club activities. Eventually, these behaviors turn into habits and become their default method for completing the tasks.

In terms of theory, Venkatesh, Thong, and Xu (2012) introduced habits as a key element in UTAUT 2. In UTAUT 2, habit is the level of how a person conducts a behavior automatically because of past experiences. Unlike conscious behavior, habits are triggered by familiar circumstances, such as academic tasks and learning environments. Due to this habitual behavior, students' use of technology may become automatic without hesitant and conscious thought. Students may not even consider alternatives if they default to using AI tools to accomplish their tasks.

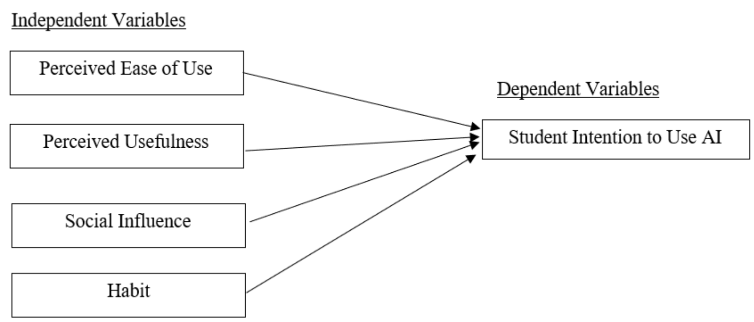
There are several research projects that support this concept. For example, Strzelecki (2023) found that students who are comfortable adopting AI tools tend to use them repeatedly. Thus, habits are formed and leads to a stronger intention to continue using them in the future. Similarly, Gwebu et al. (2014) demonstrated that habit plays a crucial role in technology continuation and reuse. When the use of technology aligns with daily routines, people will feel less hesitant and continue to use it automatically.

UTAUT2 is the only theory that uses "habit" as an element to predict the behavioural intention. Besides that, students' behaviour is frequently impacted by repeated experience and daily use. Thus, UTAUT2 is suitable for investigating the use of AI tools in academic settings.

In the Malaysian university context, more students rely on AI tools for academic or extracurricular purposes. For example, students use AI tools to help them write assignments. Besides, they will also use AI tools to plan events or brainstorm ideas. So, when these behaviors are repeated from time to time, habits will be formed. Then, their intention to continue using AI becomes stronger, even without any external encouragement. Therefore, Habit is considered a critical factor in this study, because it may significantly influence the students' intention to use AI tools.

2.3 Proposed Conceptual Framework

Figure 2.3 Conceptual Framework



For examining the elements influencing students' intention to use AI tools in higher education, this conceptual framework is essential. There is a detailed explanation of the relationship between the DV (SI) and the IV (PEU, PU, SoI, and HB). This model, that based on the TAM, UTAUT, and UTAUT2 models, states that SI are influenced by SoI, HB, and perceptions. According to TAM, PU evaluates how much students believe utilizing AI tools enhances their academic performance, while PEU evaluate how straightforward they view using AI tools to be (Phua et al., 2025). These two elements are crucial for comprehending why people adopt new technology, and they usually correlate favourably. Students are more likely to see them as useful when students believe AI tools are simple to use, they are more likely to see them as useful. SoI, according to UTAUT, happens when students observe other students using AI technologies or when they receive assistance from teachers. As a result, they utilize AI tools in their curriculum because they see them as advantageous (Venkatesh et al., 2012 as cited in Hussain et al., 2025). Such normative pressures can have significant effect on the adoption of technology in educational environments. Finally, HB, which was adopted from UTAUT2, describes how automatic the use of AI technologies becomes due to repeated exposure and past usage experience (Venkatesh et al., 2012). Users who use frequently have a higher chance to continue integrating AI-based tools into their academic routines, like Grammarly, ChatGPT, or adaptive learning systems. By identifying these components, strategies can be created and put into place to guarantee the long-term and successful application of AI in learning environments.

2.4 Hypothesis Development

2.4.1 Relationship between Perceived Ease of Use and Student Intention to Use AI

Davis (1989) created the TAM, a generally recognised paradigm for explaining users' behavioural intentions to adopt technology. In TAM, PEU refers to a person's idea that using a system would be easy to comprehend. For example, student more likely to use AI in their academic learning and extracurricular when they feel that AI technology is user-friendly, and simple to understand.

In numerous prior investigations, TAM served as a theoretical framework to examine the impact of PEU behavioural intention. Students' intentions to employ AI technology in their academic pursuits are significantly influenced by their PEU. The influence of PEU behavioural intention was investigated using TAM as a basis for theory (Hamadneh, 2024; Wu et al., 2024).

Nevertheless, According to Bakhadirov et al. (2024), PEU and desire to employ AI are not significantly correlated. The study was different from previous study because it focusses on the adoption of AI among the lectures at private schools while previous study is more about the adoption of AI among the students at university. Thus, the difference of characteristics has different results among adoption of AI.

According to studies, TAM is suitable to investigate the effect of PEU on students' desire to utilise AI, especially in the setting of colleges and universities, considering these conflicting results. This is due to university student are more inclined to use AI when AI easy to use. Therefore, considering earlier studies, the following theory could be put forward:

H_1: There is a significant relationship between PEU and Malaysian University students' intention to use AI.

2.4.2 Relationship between Perceived Usefulness and Student Intention to Use AI

In TAM, one of the key components is PU. A person's belief that utilizing a specific technique would enhance their grades in school can be assessed by PU. PU shows how helpful university students think AI technologies are for helping them with their academic learning such as researching, organization information and help them to solve the academic challenges.

Since PU is the level of belief that a person has that utilising a system would help them do better. So, it is often acknowledged that students' intentions to utilise AI technologies for learning and academic assignments are significantly influenced by PU. The results of the study show that PU has a beneficial effect on the drive to embrace AI (Wang et al., 2023; Jeong et al., 2024).

However, Wu et al. (2024) claims that behavioral desire to employ AI is not significantly influenced by PU. The study focuses on foreign language learners to improve their learning outcomes; it is hoped that AI can help them in their academic learning. This is due to the differences in sample population, AI applications fields and the methods of using AI may affect the intention of using AI Tools.

The TAM says that PU is very important in determining how student will behave. This suggests that learners are more willing to embrace AI technology when they think it can enhance their extracurricular and academic success. In addition, to better understand the interactions between PU and students' desire further research is required to employ AI in a learning environment. Thus, the following theory might be put out in conjunction with earlier research:

H_2: There is a significant relationship between PU and Malaysian University students' intention to use AI.

2.4.3 Relationship between Social Influence and Student Intention to Use AI

In UTAUT, one of the elements is social influence. It is defined as how much a person believes that people who are close to them think they should adopt a certain technology (Venkatesh et al., 2003). It plays a key role in affecting behavioral intention, especially among students in universities. This is because students normally follow the opinion of their friends and lecturers when they are deciding whether want to use the new technology to complete their tasks.

UTAUT has served as a theoretical foundation to examine the impact of social influence on behavioral intention. The results have shown that social influence had a positive and significant impact on students’ intention (Changalima et al., 2024; C et al., 2024). These findings confirm that peer and lecturer encouragement can affect student intention to use AI.

However, not all studies show consistent results. Unlike other researchers, Zamrin (2023) found that behavioral intention was not impact by social influence. This difference may arise due to technology type (e-wallet vs. AI tools) or the user base (the general public vs. students).

UTAUT is particularly well-suited for this research compared to TRA and TPB because it provides a technology-specific and social behavior-oriented explanation of how perceived expectations from influential people (such as peers or lecturers) influence students' intention to use AI tools. Therefore, based on the theoretical foundation of UTAUT and the results from previous research, the following hypothesis can be proposed:

H_3: There is a significant relationship between SoI and Malaysian University students’ intention to use AI.

2.4.4 Relationship between Habit and Student Intention to Use AI

In UTAUT2, Habit is defined as the degree to which individuals based on prior experience, tend to automatically perform their behaviors (Venkatesh et al., 2012). When technology use becomes daily routine, users may continue using it without thinking too much. Students may often use and interact with AI tools in universities. Thus, UTAUT 2 is more suitable to study the student's intention to use AI tools.

Previous studies have applied UTAUT2 to investigate the impact of habit on behavioral intention. The findings confirmed that repeated use of technology will form a habit and increase their intention to use that technology (Strezelecki, 2023). Moreover, the results also found that students' intention to use AI was significantly impacted by habit (C et al., 2024; Sadiq et al, 2025).

However, Zhu et al. (2024) conducted a study using PLS-SEM among 226 university students from China and found that while habit significantly influenced actual usage behavior, it did not significantly affect behavioral intention. This may be because AI is still in its developmental stages in some academic settings, and habitual use has not yet been fully established.

UTAUT2 is more suitable for this study because it is one of the few models that explicitly incorporates habit as a factor of behavioral intention. Habit formation becomes a critical factor as students increasingly interact with AI in their academic routines. Based on theoretical foundation and conflicting findings, it is crucial to examine how habit affects the university students' intention to sue AI in the Malaysian context. Thus, this study proposes the following hypothesis:

H_4: There is a significant relationship between HB and Malaysian University students' intention to use AI.

2.5 Chapter Summary

In this chapter, we have covered the underlying theories, the definition of the variables. Besides, we have also developed the hypothesis and the conceptual framework to discuss the relationship between DV and IVs.

CHAPTER 3: METHODOLOGY

3.0 Introduction

This chapter will discuss the research methodologies. The research design, sample methodology, data gathering technique, and suggested data analysis tools will all be covered.

3.1 Research Design

We use a quantitative research methodology, focusing primarily on statistical analyses utilizing closed-ended questions. Respondents were given a set of pre-defined answer alternatives to ensure that all the responses were consistent and easy to compare. Moreover, this study uses a descriptive research design, which describes the traits of things, people, or organizations to "paint a picture" of the given context (Zikmund et al.,2009). Thus, our study aims to give an in-depth overview of the characteristics of Malaysian university students for the usage of AI tools in extracurricular or academic contexts. Specifically, this study examines how students' intentions are impacted by four factors, which are PEU, PU, SoI, HB. In addition to identifying current trends and linkages between significant factors, this descriptive approach allows for the clear and accurate statement of students' opinions and behaviors about the employment of AI in higher education.

3.2 Sampling Design

3.2.1 Target Population

The study's target population consists of the varied group of people being investigate. The most crucial step before beginning any study is determining who our target demographic is. Our studies have concentrated on Malaysian universities in the education sector. About 1.1 million students are enrolled in these institutions overall, with roughly 420,000 students attending private universities and roughly 681,000 students attending public universities (Ashraf, 2024). Thus, students enrolling in Malaysian public or private universities were identified as our target population.

3.2.2 Sampling Frame and Sampling Location

The group list selected for sample is known as the sampling frame. As is well known, there are a lot of public and private students in the community, making it difficult to obtain a comprehensive sample frame. Consequently, we lack the sample structure necessary to count all public and private students. We have selected sample locations in Kuala Lumpur, Selangor, Pulau Pinang, Perak, and others for the study. Due to the presence of Malaysia's premier institutions, Kuala Lumpur, Penang, and Selangor are the country's most desirable student towns (Nikokaren, 2024). Universiti Sains Malaysia (USM), Malaysia's main public university who allocated in Penang, is a renowned research organisation that frequently works on technological advances and artificial intelligence (AI) studies (Hoe, 2020). In Perak, it has the university like UTAR Kampar Campus which has over 20,000 students (UTAR, 2025). Considering financial limitations or a lack of access to the latest innovations, these students may have varying AI experiences. Therefore, Students at these universities have a strong technological framework that can make them excellent for investigating AI, which may help the public by examining the problems that students experience.

3.2.3 Sampling Elements

Our study's target demographic consists of students enrolled in either public or private universities. People who are 18 years of age or above are regarded as adults and may be enrolled in higher education. Therefore, the response can be deemed appropriate. Thus, the survey of our study will be answered by students from public or private universities who are aged 18 and above.

3.2.4 Sampling Technique

Non-probability sampling is utilized in our research. This is because the enormous number of public and private students makes it challenging for us to establish a sample frame. Convenience sampling was employed in this study because it facilitated quicker and more effective data collection. This technique allows us to contact respondents such as our friends, classmates, and any students at public and private universities who are the easiest to reach.

Additionally, to ensure a balanced representation of the student population, we used a quota sampling technique. Our goal was for 50% of responders to be from public universities and 50% to be from private universities. This technique not only helped to ensure the diversity of perspectives but also kept the sampling process feasible.

3.2.5 Sampling Size

Undergraduate students from public and private institutions will participate in our survey. Malaysia boasts a wide higher education system, with nearly 1.1 million students from public and private university. Krejcie and Morgan's (1970) table indicates that since the population is greater than one million, our sample size will be 384.

Table 3.2.5: Krejcie & Morgan Table

N	*S*	*N*	*S*	*N*	*S*
10	10	220	140	1200	291
15	14	230	144	1300	297
20	19	240	148	1400	302
25	24	250	152	1500	306
30	28	260	155	1600	310
35	32	270	159	1700	313
40	36	280	162	1800	317
45	40	290	165	1900	320
50	44	300	169	2000	322
55	48	320	175	2200	327
60	52	340	181	2400	331
65	56	360	186	2600	335
70	59	380	191	2800	338
75	63	400	196	3000	341
80	66	420	201	3500	346
85	70	440	205	4000	351
90	73	460	210	4500	354
95	76	480	214	5000	357
100	80	500	217	6000	361
110	86	550	226	7000	364
120	92	600	234	8000	367
130	97	650	242	9000	368
140	103	700	248	10000	370
150	108	750	254	15000	375
160	113	800	260	20000	377
170	118	850	265	30000	379
180	123	900	269	40000	380
190	127	950	274	50000	381
200	132	1000	278	75000	382
210	136	1100	285	1000000	384

Note.—*N* is population size. *S* is sample size.

Source: Krejcie & Morgan, 1970

3.3 Data Collection Method

3.3.1 Primary Data

Primary data are those that are chosen in accordance with the study's goals, originate from the original sources, and provide personal knowledge relevant to the subject. To collect primary data for our study, we created a questionnaire and sent it to participants online through platforms like Instagram, Microsoft Teams, WhatsApp, and others.

3.3.2 Secondary Data

We used studies, publications, and journals conducted by others, including Google Scholar, ResearchGate, and ScienceDirect, to obtain secondary data since they offer trustworthy, current research, which makes them important resources for guaranteeing the level of quality and applicability of our study.

3.4 Research Instrument

To ensure that the facts revealed become pertinent data, high-quality tools must be used for the study topic's collection, analysis, and examination. This suggests that the information gathered needs to be accurate and legitimate (Sukmawati, 2023). In our research, a questionnaire is used as the main research instrument. This method allowed for the rapid collection of data from key respondents and produced well-structured, easily analysed responses. The main objectives of this study is to investigate the effects of PU, PEU, SoI, and HB on the intentions of universities students to use AI.

3.4.1 Questionnaire Design

In this study, Google Form will be used to create an online questionnaire and share it to the respondents. The questionnaire consists of 27 questions organized into 6 categories, with 1 category specifically for demographic survey.

Morover, we use closed-ended questions to provide respondents with a range of options. This questionnaire design facilitates the gathering and analysis of responses. This can help us in analysing data more quickly. We use ordinal and nominal scales for the six demographic profile questions in Section A, which are gender, age, education level, university type, university location, and duration of using AI tools. In Section B, participants are required to rate their intention to use AI on a 5-point Likert scale. Furthermore, all independent variables will be evaluated in Section C, D, E, F respectively. All the items are also will be ranked using 5-point Likert scales.

We use 5-point Likert scales because it provides a good balance between simplicity and detail. It offers a richer diversity of answers than the 3-point and 4-point scales, which might be too restrictive and fail to adequately represent the diverse range of respondent opinions. On the other hand, the 5-point scale is easier for respondents to understand and respond compared to 6-point and 7-point scales. The inclusion of midpoint scales in 5-point scales is considered as an advantage because it allows respondents to remain neutral if they are neither inclined to agree nor to disagree. Also, some researchers suggest that the 5-point scale can reduce misunderstanding, improve response rates and quality, making it a useful and reliable option for survey-based research (Russo et al., 2021).

Reliability of the item in each variable:

Student Intention (SI)

In our questionnaire design, we have adapted the behavioural intention constructs from Maican’s and Park’s studies. (Maican et al., 2023; Park, 2009). The behavioural intentions CA of 0.835 and CR of 0.840 both indicate good dependability and a high level of internal consistency. The AVE of 0.752, which was higher than the 0.50 criterion, demonstrated validity of convergence. Further supporting the measurement model's robustness was the model fit, this was below the 0.08 criterion with an SRMR value of 0.07. Further confirming criterion validity were the relationships between behavioural intention and the UTAUT2 concept of habit and social influence (Maican et al., 2023). Besides that, CA values above 0.80 and the behavioural intention construct's excellent internal consistency demonstrated its high degree of dependability. The behavioural intention items loaded on a different factor, according to exploratory factor analysis (EFA), and convergent validity was demonstrated by the fact that each of them had factor loadings higher than 0.7. The relationships between behavioural intention and the two TAM components—PU and PEU—further supported the validity of the criteria (Park, 2009).

Perceived Ease of Use (PEU)

We have used Rahman's studies to construct the PEU. In Rahman's studies, it shows that the CR and CA of PEU is 0.917 and 0.915 which demonstrate superior dependability. Besides, AVE is 0.689 which is higher than the 0.50 cut-off value. This indicates that the constructs account for enough of variance in their indicators. Thus, these findings show that the concept of PEU, as modified from Rahman's investigations, has excellent reliability as well as strong convergent validity, making it a trustworthy and valid measure for this study (Rahman, 2023).

Perceived Usefulness (PU)

In addition, in questionnaire design, we have used Rahman's studies to construct the perceived usefulness. The CR and CA of PU in Rahman's studies is 0.910 and 0.908 which show the solid internal consistency. While AVE for perceived usefulness is 0.716 which also higher than 0.50 cut-off value shows the solid reliability and convergent validity to measure these studies (Rahman, 2023).

Social Influence (SoI)

We have adapted the constructions of social influence from 2 sources which are from Changalima’s and Kim’s studies. Both Changalima's and Kim's studies used different statistical tests to show the reliability of the Social Influence construct. The CA in Changlima’s studies was 0.956, and in Kim’s studies was 0.838, showing a excellent internal consistency. Besides that, the CR are 0.914 and 0.902 in both studies. Additionally, the AVE is 0.515 in Changalima’s studies and 0.755 in Kim’s studies. This result shows good internal consistency (Changalima et al., 2024; Kim et al., 2024). Therefore, the constructs that we use for social influence in our study are reliable.

Habit (HB)

Moreover, in our questionnaire design, we have also adapted the constructs of habit from both Maican's and Rahim's studies. The CA of Maican and Rahim are 0.618 and 0.701 respectively, which consider acceptable. Furthermore, Maican’s CR is 0.796 and Rahim’s CR is 0.793, both showing a good internal consistency. Moreover, the AVE is 0.566 for Maican’s study and is 0.618 for Rahim’s study. which confirmed the convergent validity (Maican et al., 2023; Rahim et al., 2022). These results show that the Habit construct is reliable.

Section A: Demographic

Variables	Adapted item	Source
Gender	Male Female	Rahman et al. (2023) and Liang & Alias (2025)
Age	18-20 21-23 24-26 >26	
Education level	Diploma Bachelor Masters & PhD	
University type	Private Public	
Location of University	Kuala Lumpur Selangor Perak Penang Others	
Duration of Using AI tools	0 year to 1 year More than 1 year to 2 years More than 2 years to 3 years More than 3 years	

Section B: Dependent Variable

Variable	Adapted Questionnaire	Source
Student Intention to use AI (SI)	1. I plan to continue using AI tools for academic or extracurricular activities. 2. I will try to use AI tools regularly for academic or extracurricular activities. 3. I intend to continue to use AI tools frequently for academic or extracurricular activities. 4. I intend to be a heavy user of AI tools for academic or extracurricular activities	Maican et al. (2023) and Park (2009)

Section C, D, E, F: Independent Variables

Variable	Adapted Questionnaire	Source
Perceived ease of use (PEU)	1. Using AI tools, academic learning or extracurricular activities become easy. 2. Using AI tools for academic learning or extracurricular activities requires less mental effort. 3. Academic learning or extracurricular activities are easy and understandable with AI tools. 4. I can easily become skillful at using AI tools for academic learning or extracurricular activities. 5. I think I will be able to learn using AI tools without the help of an expert.	Rahman et al. (2023)
Perceived usefulness (PU)	1. Using AI tools for academic learning or extracurricular activities enables me to achieve learning and extracurricular objectives effectively. 2. Academic learning or extracurricular activities using AI tools improve my performance 3. Using AI tools is useful to provide access to information 4. Using AI tools for academic learning or extracurricular activities will increase my productivity.	Rahman et al. (2023)
Social influence (SoI)	1. People who important for me think I should use AI tools 2. People who influence my behavior believe that I should use AI tools 3. People whose opinions I value prefer me to use AI tools. 4. My friends have already adopted and are using AI tools for academic or extracurricular activities.	Changalima et al. (2024) and Kim et al. (2024)

Habit (HB)	1. Using AI tools to complete my task has become a habit for me. 2. An AI tools will be my first option whether an enquiry or seek information regarding academic or extracurricular matters 3. I feel comfortable using AI tools to look for a solution regarding academic or extracurricular matters 4. Using an AI tools is something I do without hesitation.	Maican et al. (2023) and Rahim et al. (2022)

3.4.2 Pilot Study

The questionnaire was circulated during the pilot study period, and a total of 30 respondents were collected. We used SPSS software to process all the data and test the reliability of each item across all variables. The pilot study's reliability test findings are shown in Table 3.4.2. The CA of Student Intention (SI) is 0.803. Besides, PEU has a CA of 0.76. For PEU, SoI, and HB, the CA were 0.815, 0.912 and 0.777 respectively. All results met the threshold of 0.7, proving the validity of every item in the survey and its suitability for a comprehensive investigation.

Table 3.4.2 *Reliability Test for Pilot Study*

	Variables	Cronbach's Alpha (CA)	No. of items	Internal Consistency
Dependent Variable (DV)	Student Intention (SI)	0.823	4	Good
Independent Variables (IVs)	Perceived Ease of Use (PEU)	0.760	5	Acceptable
	Perceived Usefulness (PU)	0.815	4	Good
	Social Influence (SoI)	0.912	4	Excellent
	Habit (HB)	0.777	4	Acceptable

Source: Data from SPSS

3.5 Proposed Data Analysis Tools

3.5.1 Descriptive Analysis

To create a demographic profile of the respondents, we will use descriptive analysis. Gender, age, level of education, university type, location, and duration of using AI tools are included in the details. Additionally, it will provide a general overview of the respondents' responses to our research variables (SI, PEU, PU, SoI, HB). In addition to mean and standard deviation, we will calculate metrics like frequency and percentage to describe the primary patterns and variability in the collection.

3.5.2 Reliability Analysis

Reliability analysis is a general statistical method for predicting the effectiveness of a system (Khare et al., 2018). It is employed to guarantee that answers to each survey item are internally consistent. The primary indicator will be Cronbach's Alpha. An adequate CA of 0.70 or higher indicates proper internal consistency (Ahmad et al., 2024). We can confirm that the results of this analysis are consistent across all the items used to assess each variable (SI, PEU, PU, SoI, and HB).

Table 3.5.2 Reliability Level

Reliability Level	Cronbach’s Alpha Range	Interpretation
Excellent	0.90 and above	Indicates very high internal consistency.
Good	0.80 - 0.89	Reflects strong internal consistency.
Acceptable	0.70 - 0.79	Indicates acceptable internal consistency.
Questionable	0.60 - 0.69	Reflects questionable internal consistency.
Poor	Below 0.60	Indicates poor internal consistency.

Source: Ahmad et al., 2024

3.5.3 Preliminary Data Analysis (Normality test, Multicollinearity test)

It is important to make sure our data is in normal distribution. This is to ensure the reliability of our regression analysis. If the kurtosis and Pearson skewness coefficients fall between -7 and +7, or between -2 and +2, the data gathered from the questionnaire can be of a normal distribution. In order for our data to be classified as having a normal distribution, we must, in essence, make sure that our values fall between these two ranges.

Furthermore, we must make sure that multicollinearity is not an issue. Since a single variable can reflect both factors when they are associated, we must ensure that our IV (PEU, PU, SoI, HB) do not have a strong correlation. Multicollinearity will be examined using tolerance values and VIF. We must ensure that the tolerance value > 0.20 and the VIF value is < 3.0 to prove that IVs are not collinear.

3.5.4 Independent Sample T-test

An extra analysis will be carried out to improve the findings' representativeness. The independent sample t-test is used to determine whether the means of two independent samples differ significantly (Choudhary, 2018). The independent sample t-test will be used in this study to determine if students at public and private universities have significantly different intentions about the usage of AI tools.

The equality of variances will be assessed by Levene's Test. If the p-value is > 0.05 in Levene's Test, equal variances are assumed; otherwise, equal variances are not assumed. The significance level (p-value) under the corresponding row will be used to interpret the result. A p-value < 0.05 will show no difference between 2 groups.

3.5.5 Inferential Analysis (Multiple Regression Analysis)

Multiple regression analysis will be used to test the hypotheses. We need to test the relationship between the DV (SI) and the four IV (PEU, PU, SoI, HB). Correlation analysis will be used to assess the direction and strength of the relationships between the variables. This technique will make it possible to assess each predictor's contribution while accounting for the influence of the others. Each independent variable's standardized beta coefficient (β), t-value, and p-value will be analyzed to see which factor is significantly affect students' intention to use AI. A p-value < 0.05 is consider a significant predictor. Moreover, the R^2 will also be presented to show the extent to which the whole collection of IVs can explain the variation in the DV. The SPSS program will be used to do the inferential analysis.

3.6 Chapter summary

In this chapter, we have covered the research and sampling strategy, data collection technique, questionnaire items utilized, and suggested data analysis methods.

CHAPTER 4: DATA ANALYSIS

4.0 Introduction

The data and analysis of the findings, that are crucial for addressing the goals of the study and bolstering the underlying ideas will be presented. The relevant data from our investigation will be analysed using the SPSS Statistics 30.0 program. The SPSS results will be presented via tables and figures. In this chapter, we will cover descriptive analysis, reliability analysis, preliminary analysis, and inferential analysis.

4.1 Descriptive Analysis

4.1.1 Respondent Demographic Profile

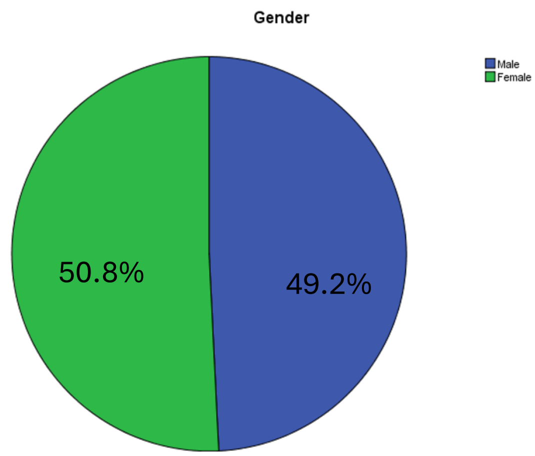
Table 4.1.1.1 Gender

Gender

	Frequency	Percent	Valid Percent	Cumulative Percent
Valid Male	189	49.2	49.2	49.2
Female	195	50.8	50.8	100.0
Total	384	100.0	100.0	

Source: Data from SPSS

Figure 4.1.1.1 Gender



According to Table and Figure 4.1.1.1 Gender, 189 of the responses, or 49.2% of the total, are male. Meanwhile, there are 195 or 50.8% of total respondents are female. This demonstrates that we may investigate the aspects that students of both gender believe influence their intention to use AI in universities.

4.1.1.2 Age

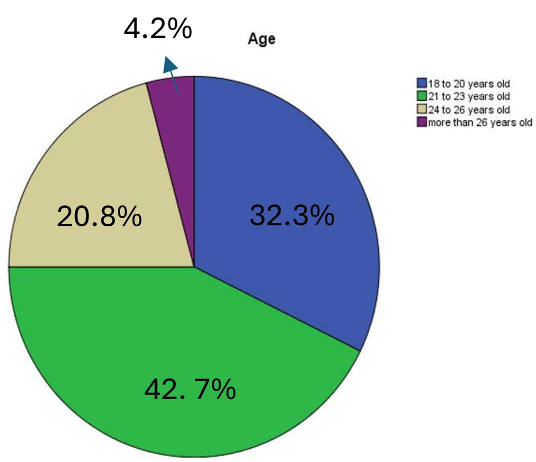
Table 4.1.1.2 Age

Age

	Frequency	Percent	Valid Percent	Cumulative Percent
Valid 18 to 20 years old	124	32.3	32.3	32.3
21 to 23 years old	164	42.7	42.7	75.0
24 to 26 years old	80	20.8	20.8	95.8
More than 26 years old	16	4.2	4.2	100.0
Total	384	100.0	100.0	

Source: Data from SPSS

Figure 4.1.1.2 Age



Most respondents who intended to employ AI in their university are aged between 21 to 23 years old was contributed 164 persons or 42.7% of the total, are show in the table and figure 4.1.1.2 Age. Those between 18–20 ages and those between 24–26 ages came in second and third, respectively, at 32.3% and 20.8%. Those respondents aged more than 26 years old contributed the lowest, which was 4.2% respectively. This indicates that the respondents have sufficient knowledge about the implementation of AI in universities.

4.1.1.3 Education Level

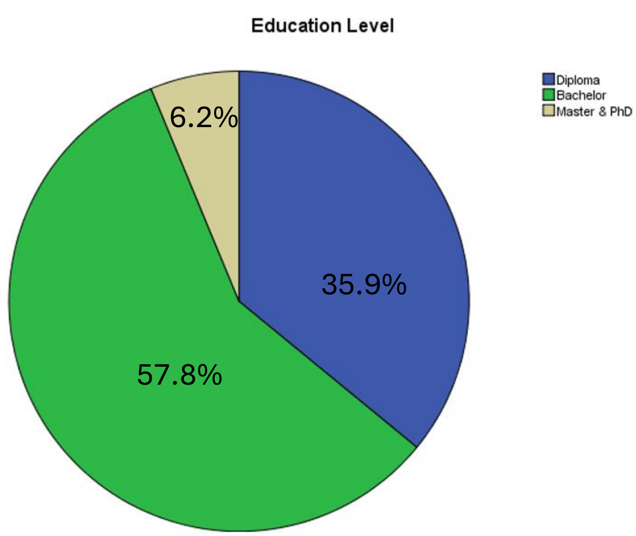
Table 4.1.1.3 Education Level

Education Level

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Diploma	138	35.9	35.9	35.9
	Bachelor	222	57.8	57.8	93.8
	Master & PhD	24	6.2	6.2	100.0
	Total	384	100.0	100.0	

Source: Data from SPSS

Figure 4.1.1.3 Education Level



The majority of respondents (222, or 57.8% of the total) want to employ AI in universities as indicated by the table and figure 4.1.1.3 Education Level. With 138, or 35.9% of the total, having a bachelor's degree, they rank second. Those respondents which are master and phD contributed the lowest, which was 6.2% respectively. This indicates that the respondents know sufficiently about the implementation of AI in universities.

4.1.1.4 University Type

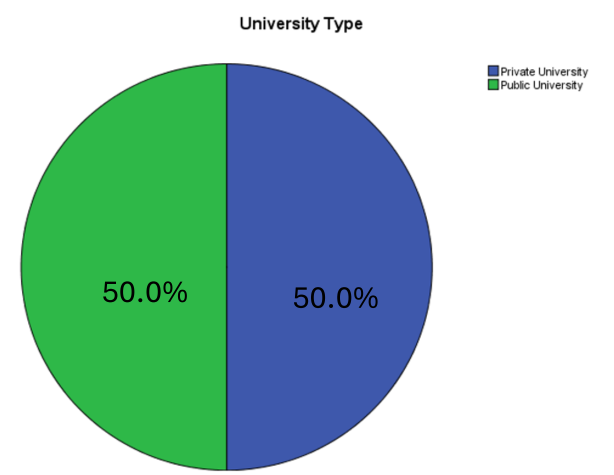
Table 4.1,1.3 University Type

University Type

	Frequency	**Percent**	**Valid Percent**	**Cumulative Percent**
Private University	192	50.0	50.0	50.0
Public University	192	50.0	50.0	100.0
Total	384	100.0	100.0	

Source: Data from SPSS

Figure 4.1.1.4 University Type



According to the table and figure 4.1.1.4 University Type, 192 respondents, or 50% of the total, are from private universities, and 192 respondents, or 50% of the total, are from public universities. In this survey, respondents from private universities and public universities equally participated in this study.

4.1.1.5 Location of University

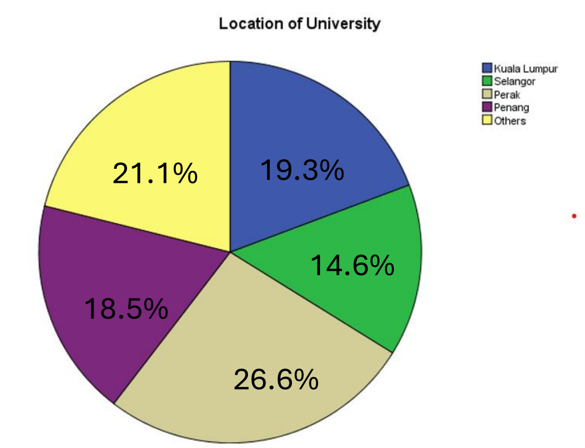
Table 4.1.1.5 Location of University

Location of University

	Frequency	Percent	Valid Percent	Cumulative Percent
Kuala Lumpur	74	19.3	19.3	19.3
Selangor	56	14.6	14.6	33.9
Perak	102	26.6	26.6	60.4
Penang	71	18.5	18.5	78.9
Others	81	21.1	21.1	100.0
Total	384	100.0	100.0	

Source: Data from SPSS

Figure 4.1.1.5 Location of University



The table and figure 4.1.1.5, Location of University, show that 102 students, or 26.6% of the total, are enrolled at Malaysian universities, making up the majority of respondents. The others come in second with 21.1% of respondents. 19.3% of respondents belong to Kuala Lumpur, whereas 18.5% of respondents come from Penang. The lowest percentages, 14.6%, come from Selangor. This indicates that the majority of the survey's contributions were from Perak.

4.1.1.6 Duration of using AI tools

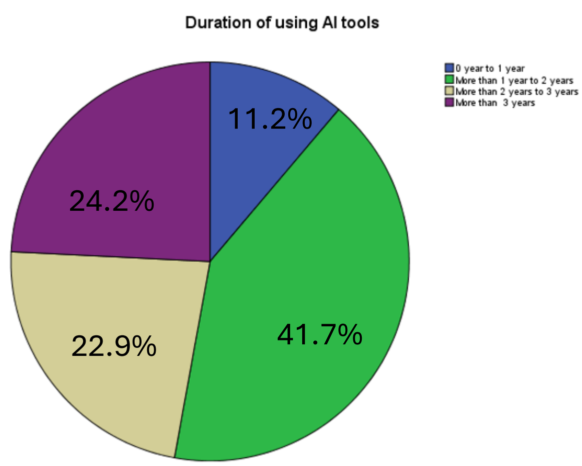
Table 4.1.1.6 Duration of using AI tools

Duration of using AI tools

	Frequency	Percent	Valid Percent	Cumulative Percent
0 year to 1 year	43	11.2	11.2	11.2
More than 1 year to 2 years	160	41.7	41.7	52.9
More than 2 years to 3 years	88	22.9	22.9	75.8
More than 3 years	93	24.2	24.2	100.0
Total	384	100.0	100.0	

Source: Data from SPSS

Figure 4.1.1.6 Duration of using AI tools



The majority of respondents, 160 students, or 41.7%, have been using AI tools for more than a year or two years, as shown in table and figure 4.1.1.6, Duration of utilizing AI tools. For students who have been using AI tools for more than 3 years comes second, which comprises 93 students, or 24.2% of the total. 22.2% of respondents are using AI tools for more than 2 years to 3 years. The lowest percentages, 11.2% of students are using AI tools for 0 year to 1 year. According to this, the majority of those surveyed had some knowledge about artificial intelligence, indicating a moderate to high level of exposure that may have an impact on their intention for using AI.

4.1.2 Central Tendencies Measurement of Constructs

Table 4.1.2 Central Tendencies Measurement of Constructs

Variables	Sample size (N)	Mean	Standard Deviation
Student Intention Average	384	4.3698	0.49141
Perceived Ease of Use Average	384	4.4698	0.50203
Perceived Usefulness Average	384	4.5645	0.48399
Social Influence Average	384	4.5000	0.57782
Habit Average	384	4.4167	0.56862

Source: Data from SPSS

According to the above table, most respondents believe AI is helpful in educational settings, with PU having the greatest mean (4.5645) and standard deviation (0.48399). SoI indicate that social variables have a moderate effect on the inclination to use AI, with a mean of 4.5000 and the biggest standard deviation of 0.57782. Furthermore, PEU and HB show relatively high meaning, which are 4.4698 and 4.4167. The PEU standard deviation is 0.50203, while the HB standard deviation is 0.56862. SI to employ AI technologies are usually positive, showing that the mean of SI, 4.3698, with a standard deviation of 0.49141.

4.2 Scale of Measurement

4.2.1 Reliability Analysis

Table 4.2.1 Result of Reliability Analysis

Variables	Cronbach's Alpha	Number of items
Student Intention	0.876	4
Perceived Ease of Use	0.908	5
Perceived Usefulness	0.895	4
Social Influence	0.923	4
Habit	0.881	4

Source: Data from SPSS

Table 4.2.1 shows that the four items measuring student loyalty have very strong reliability, with the reliability test for SI having a CA of 0.876, falling between α = 0.80 to 0.95. In addition, the CA for PEU is 0.908, falling between α = 0.80 to 0.95. As a result, the five items that measure PEU have excellent dependability. Additionally, the reliability test for PU revealed a CA of 0.895, which lies between α = 0.80 and 0.95, suggesting that the four items assessing PU had extremely strong reliability. Furthermore, the reliability test for SoI revealed a CA of 0.923, which lies between α = 0.80 and 0.95, suggesting that the four items assessing SoI had extremely strong reliability. Finally, CA for HB's reliability test was 0.881. Given that the CA value of 0.0.881 falls between α = 0.80 and 0.95, the four items measuring HB have extremely acceptable reliability.

4.3 Preliminary Data Analysis

4.3.1 Normality Test

Table 4.3.1 Result of Normality Test

Variables	Skewness	Kurtosis
Dependent variable: Student Intention (SI)	-0.576	1.305
Independent variable 1: Perceived Ease of Use (PEU)	-0.643	0.217
Independent variable 2: Perceived Usefulness (PU)	-0.854	0.395
Independent variable 3: Social Influence (SoI)	-1.467	4.065
Independent variable 4: Habit (HB)	-1.089	2.117

Source: Data from SPSS

This study's data set has a normal distribution. In this table, it indicates that all the variables of this study, which are SI, PEU, PU, SoI, HB have skewness and kurtosis values that fall within the predetermined range. Normality tests are performed to ensure that the data distribution is regular. The skewness of a variable's distribution reveals how symmetrical are. The kurtosis shows whether the distribution of data is uniform or has peaks (Pulka, 2022). In short, skewness and kurtosis are two measurements that can be used to determine whether data is natural. Therefore, the collected data are considered regularly distributed if the skewness falls between -2 to +2 and the kurtosis values fall between -7 to +7.

4.3.2 Multicollinearity Test

Table 4.3.2 Result of Multicollinearity Test

Independent Variables	Collinearity statistics	
	Tolerance	VIF
Independent variable 1: Perceived Ease of Use (PEU)	0.713	1.403
Independent variable 2: Perceived Usefulness (PU)	0.679	1.472
Independent variable 3: Social Influence (SoI)	0.600	1.668
Independent variable 4: Habit (HB)	0.669	1.494

Source: Data from SPSS

There is no multicollinearity among the IV, as evidenced by tolerance values that are greater than 0.20 and VIP lower than 3.0. This is because when the tolerance value is less than 0.20 or more than 0.20 imply the absence of collinearity among the independent variables. It is further advised that the VIF value remain below 3.0 to prevent the multicollinearity issue. In addition, the multicollinearity test was established to ascertain whether the regression model identified a relationship among the IV. In other words, multicollinearity arises from a substantial correlation among two or more independent variables. The singular variable denotes these variables if they exhibit correlation (Shrestha, 2020). Thus, in order to ascertain the absence of multicollinearity, it is essential to examine it during the preliminary data analysis utilising VIF and Tolerance Values Multiple linearity issues arise.

4.4 Independent T-test

Table 4.4 Result of Independent T-test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std.Error Difference	95% Confidence Interval of the Difference	
									Lower	Upper
Student Intention to use AI	Equal variances assumed	0.036	0.850	0.104	382	0.917	0.00521	0.05022	-0.09353	0.10395
	Equal variances not assumed	-	-	0.104	379.511	0.917	0.00521	0.05022	-0.09354	0.10395

Source: Data from SPSS

According to Levene's tests, students at both public and private universities had an identical variance in their mean intention to utilize AI which is the t-value for the report is 0.104. In other words, Sig. 0.850 from the table is above the alpha value of 0.05. Thus, it shows that the variances are equal and the t-value under equal variances assumed 0.104 should be reported.

Besides, private and public universities have no significant differences in using AI Tools is supported by the data. The p-value under equal variance assumed is 0.917. The p-value of 0.917 is significantly higher than the alpha value of 0.05. Therefore, the p-value (sig.(2-tailed)) under equal variance is thought to be reported, which is the cause of this.

This finding suggests that students in both public and private universities share similar mindsets and intentions in adopting AI tools. One possible reason is that today's university students belong to the same digital generation, where technology has always been part of their daily lives. Their digital skills and exposure to online platforms may reduce the gap between public and private institutions. Moreover, students' personality traits may shape more intention to use AI than the resources provided by the university (Korkmaz & Akbiyik, 2024; Kaya et al., 2022). This challenges the common perception that private universities, due to their focus on cost-saving, may provide less support than government-funded public universities. However, the results suggest that institutional differences are only minor drivers of AI adoption. This is because students' intention to use AI remains the same regardless of the type of university they attend.

4.5 Inferential Analysis (Multiple Regression Analysis)

The variance in a DV (SI) is indicated by a combination of IV (PEU, PU, SoI, HB).

Table 4.5.1 Model Summary

Model	R	R square	Adjusted R Square	Std. Error of the Estimate
1	0.567[a]	0.321	0.314	0.40705

a. Predictors: (Constant), Habit Average, Perceived Ease of Use Average, Perceived Usefulness Average, Social Influence Average

b. Dependent Variable: Student Intention Average

The R value is 0.567, showing IVs (PEU, PU, SoI, HB) and DV (SI) has a moderate positive correlation.

The R-squared in this study is 0.321. This indicates that 32.1% of SI' variance can be explained by the PEU, PU, SoI, and HB. The remaining 67.9% (100%-32.1%) cannot be explained. In other words, this study has not considered other significant variables that are relevant in explaining student intentions.

Table 4.5.2 ANOVA

Model		Sum of Square	df	Mean Square	F	Sig.
1	Regression	29.692	4	7.423	44.800	0.000[a]
	Residual	62.798	379	0.166		
	Total	92.490	383			

H_1 = The four independent variables (PEU, PU, SoI HB) significantly explain the variance in Student Intention to use AI.

Based on Table 4.5.2, the p-value < 0.05, suggesting the significance of the F-statistic. The model employed in this study provides a clear description of the relationship between dependent and predictor variables. Therefore, a significant amount of the variation in Student Intention to use AI can be attributed to independent variables (PEU, PU, SoI, HB). The data supports the alternative hypothesis.

Table 4.5.3 Coefficients

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	Beta	Std. Error	Beta		
(Constant)	1.436	0.235		6.109	0.000
Perceived Ease of Use Average	0.384	0.049	0.393	7.829	0.000
Perceived Usefulness Average	0.068	0.052	0.067	1.306	0.192
Social Influence Average	0.033	0.046	0.039	0.720	0.472
Habit Average	0.171	0.045	0.198	3.821	0.000

Source: Data from SPSS

Based on Table 4.5.3, only PEU and HB are the significant factors. This is because the p-values of these two IV is <0.05. This indicates that if students who think that AI is user-friendly have developed the habits, they will more willing to use it. In contrast, SoI (p = 0.472) and PU (p = 0.192) have no significant impact on SI. This is because the p-values are > 0.05.

Regression equation:

y = a + b1 (x1) + b2 (x2) + b3 (x3) + b4 (x4)

y = SI

x1 = PEU

x2 = PU

x3 = SoI

x4 = HB

SI = 1.436 + 0.384 (PEU) + 0.068 (PU) + 0.033 (SoI) +0.171 (HB)

Highest Contribution

PEU is the most significant factor that SI. It has the highest standardized beta coefficient of 0.393. Moreover, the relationship is significant ($p < 0.001$). This result provides strong evidence for the impact of PEU on students' intention.

Second-Highest Contribution

HB is the second most powerful predictor. It has a standardized beta value of 0.198, This suggests that students' intentions to use AI tools are also significantly shaped by their habitual behavior. In addition, the relationship is statistically significant ($p < 0.001$) further supports its significance as a major influencing factor.

Third-Highest Contribution

PU is the third highest contribution to this study because the standardized beta coefficient is 0.067. Furthermore, after accounting for other factors, this relationship's explanatory power is weak, as it is not statistically significant ($p = 0.192$).

Lowest Contribution

SoI is the least significant factor to affect SI. This is because the standardized beta coefficient is 0.039. When other factors like habit and ease of use are considered, the non-significant p-value ($p = 0.472$) indicates that peer or social expectations do not significantly influence students' usage intentions in this context.

CHAPTER 5: DISCUSSION, CONCLUSION, AND IMPLICATION

5.0 Introduction

This chapter will discuss the findings of the factors impacting Malaysian university students' intention to use AI. In this chapter, we will cover major findings, consequences, study limitations, and suggestions for further research.

5.1 Discussion of Major Findings

Table 5.1.1 Hypothesis Results

Variables	Hypothesis Result
Perceived Ease of Use (PEU)	Significant
Perceived Usefulness (PU)	Not significant
Social Influence (SoI)	Not significant
Habit (HB)	Significant

Source: Data from SPSS

5.1.1 Perceived Ease of Use and Student Intention

Based on hypothesis H_1, Malaysian university students' intention to use AI and PEU are significantly correlated. With a normalized coefficient for PEU of $\beta = 0.393$ and a p-value below 0.05, the multiple regression analysis demonstrated that the association is significant. Since PEU has a substantial influence on Malaysian university students' intention to use AI, H_1 is thus supported. These results support Research Objective 1, which seeks to ascertain if students' inclination to employ AI technologies in academic and extracurricular activities is influenced by PEU.

Studies by Davis (1989) and Venkatesh & Bala (2008), who also found that PEU had a big influence on technology adoption are in line with the studies. One reason for this significant influence could be that Malaysian students are more prone to rely on simple solutions because of their demanding academic schedules and lack of time to acquire sophisticated tools. All things considered, this study highlights how important it is to consider usability while urging students to adopt AI.

5.1.2 Perceived Usefulness and Student Intention

According to hypothesis H_2, Malaysian university students' intention to use AI and PU are significantly correlated. A standardized coefficient for perceived usefulness of $\beta = 0.067$ and a p-value greater than 0.05 indicated that the association is not statistically significant, according to multiple regression analysis. Therefore, H_2 is not supported, suggesting that PU are not significantly impact Malaysian university students' intention to use AI. However, these results do not support Research Objective 2, which determined whether PU affects students' intention to use AI technologies in academic and extracurricular activities.

Compared to Venkatesh et al. (2003), this research shows smaller impact, which might be because students are not fully aware of or benefit from the long-term academic advantages of AI tools. One reason could be that students are more affected by the technologies' usability than by their possible benefits. Instead of evaluating the overall quality or dependability of the content provided, many students could focus on the immediate benefits, such as how easy it is to get information, how long it takes to conduct research, or how quickly they can complete projects.

5.1.3 Social Influence and Student Intention

According to hypothesis H_3, Malaysian university students' intention to use AI and SoI is significantly correlated. The relationship is not significant based on the results of the multiple regression analysis. The p-value is higher than 0.05 and the normalized coefficient for SoI is 0.039. Thus, H_3 is not supported. For our These results do not support Research Objective 3, which seeks to ascertain if SoI affects students' intention to use AI tools in extracurricular and academic activities.

This finding differs from earlier studies that emphasized the importance of SoI during the initial stages of technology adoption (Venkatesh et al., 2003). Furthermore, it contradicts the findings of earlier research that indicated SoI significantly affects behavioural intention (Changalima et al., 2024; C et al.,2024). One possible explanation for these findings is that Malaysian university students perceive AI use as a personal decision rather than one that is influenced by others. This is because students have more access to information, allowing them to investigate and evaluate the new technologies independently (Ng, 2012). As a result, they may more emphasize their intrinsic motivation, learning preferences, and their own judgements instead of following their peer suggestions (Deci & Ryan, 2000). Other than that, they might already have their own preferences or worries about the ethical implications of AI, making them less dependent on social influence (Dwivedi et al., 2023).

5.1.4 Habit and Student Intention

The hypothesis H_4 suggested that Malaysian university SI to utilize AI is significantly influenced by their HB. The regression analysis showed that the standardized coefficient for Habit is 0.198. The association has significance when the p-value is lower than 0.05. Therefore, H_4 is supported. This confirmed that HB and Malaysian university SI to adopt AI are significantly correlated. These findings support Research Objective 4, which aims to determine whether HB influences SI to use AI tools in academic and extracurricular activities.

This result is consistent with the UTAUT2 framework (Venkatesh et al., 2012), which highlights habit as a crucial component of technology use. It suggests that the more natural and consistent AI use gets, the more likely students are to remain with it. Which is in line with earlier studies like Strezelecki (2023) and Sadiq et al. (2025). Students who use digital platforms regularly in Malaysian higher education may form habits related to AI tools that will eventually reinforce their use. Therefore, to increase the degree of technology adoption and integration, it is important to early and regular exposing students to AI tools in an academic setting. this is because this allows them to become familiar with technology and form their own usage habits.

5.2 Implications of the Study

First, this study showed that the PEU has significantly impact on SI to adopt AI in their academic learning and extra-curricular. This demonstrates that many students are more likely to use AI tools to enhance their academic learning, such as learning outcomes accuracy and efficiency. When AI tools are designed to be easy to use and understand, students are more likely to use them regularly and with comfort. Hussein and Hilmi (2022) claim that when the learning tools is simple to use and lessen mental load, Malaysian university students are more likely to use them for their daily academic learning as ease AI tools can reduce cognitive strain and boosting system confidence. Therefore, both public and private universities should highlight the benefits of AI tools for learning, such as providing students with tutorials or actual experience. So that, university can increase the student adoption to use AI tools and be more productive digital learning spaces like online meeting or digital classroom that make it easier to use.

Besides, this study highlights that PU has not significantly impact on SI to use AI. According to recent research that conducted in Malaysia, PU has been shown to have a moderate effect size when compared to other factors like contentment that despite having a favourable association with the adoption of AI (Yusoff et al., 2025). This finding raises the possibility that Malaysian university students are still unaware of the direct benefits of using the AI tools to improve their academic learning and performance. For example, getting general knowledge, understanding intricate ideas, and getting immediate assistance to improve learning and achievement. In short, to improve the PU and student intention to use AI, educational organizations and policy makers should engage in proving the concrete academic benefits by using the AI tools such as doing the testing or data analysis. MOHE could establish clear guidelines for the successful adoption of AI, fund innovations in AI-integrated teaching, and launch national AI literacy programs. Universities could, in the meantime, develop specialized hubs for student interaction with AI, integrate AI-related modules across disciplines, and test AI-driven learning platforms.

In addition, SoI show that it is not significant impact on SI to use AI. This is due to students making more independent and value-oriented actions when choosing to use AI tools and it is predicted to be swayed by peers or instructors. For instance, AI tools can be used in event planning, creative content creation, idea generation, concept clarification and so on in student academic learning and extracurricular. In other words, universities should consider personal interest to personalising AI learning campaigns like how to use AI to improve the academic performance and efficiency as opposed to group approval. Educators and policymakers can incorporate autonomous AI modules into their e-learning platforms or showcase individual student achievement stories utilizing the AI tools.

Lastly, this study highlights that HB is significantly impact on SI to use AI. This demonstrates that students are more inclined to remain using AI technologies if they find them more convenient and pleasant in their daily activities. Moorthy et al. (2019) emphasize that habit is the strongest predictor of technology. students' usage behaviour was strengthened positively with regular and repetitive usage of learning technology tools. Therefore, institution and policymakers can encourage student to use AI tools in their daily academic learning and extracurricular. For instances, involving intelligent tutoring programs, grammar checkers powered by AI or AI quiz creators to students' assignments regularly. As a result, using the AI tools in student academic learning regularly can progressively develop constructive habits and with increased habitual use, students' desire to consistently.

5.3 Limitations of the Study

First of all, the sample is restricted to Malaysian university students, therefore the results' generalizability to other populations or educational contexts would be limited. Because of this, the results might not apply to other groups, like students in other nations, learners who do not attend college, or working professionals. People's perceptions and plans for using AI tools may be influenced by the wide variations in educational systems, technology exposure, and cultural attitudes toward AI.

Second, the study used self-reported data, which is subjective by nature. Potential bias is introduced when individuals give responses that reflect their ideal or socially acceptable behaviour rather than their actual behaviour or beliefs. This is particularly true for variables like habit or social influence.

Thirdly, a cross-sectional methodology is used to the study collected data at a certain point in time. As students get more proficient with AI tools or as new technologies are introduced, it becomes increasingly difficult to track how their intentions or perceptions change. As a result, the study is unable to verify whether the associations found are stable over time or impacted by temporary events, such as recent exposure to AI in a particular classroom.

Lastly, the study only examined four indicators—PU, PEU, SoI, and HB—that are based on well-known theories of technology acceptance. However, certain crucial components were omitted, including information about students' digital literacy, degree of AI trust, past experiences, institutional support, and even privacy. There may also have a big influence on students' intention to employ AI tools for the overlooked. Even though these limitations are acknowledged, they add valuable guidance for future research rather than diminishing the significance of the results.

5.4 Recommendations for Future Research

First, future studies require to think about increasing the sample size. For example, future research can included participants from different countries, education levels, or academic programme. This would help the findings become more applicable to different circumstances. Furthermore, a more diverse sample can provide a more comprehensive result. This is due to the possibility that various demographics may have varied experiences with AI technologies.

Second, future studies can incorporate more objective metrics with personal information. For instance, researchers can monitor login frequency and gather system-generated usage data from AI platforms. This can help them to gather more accurate data. This will be very useful especially to examine SoI and HB that are frequently influenced by actual behavior rather than just perception.

Third, future research can use a vertical design to observe how the intents of the students change over time. For instance, researchers can distribute the questionnaire to the students at the beginning, middle and the semester's end to monitor how students' intentions change over time.

Lastly, future research can also consider adding other variables in their studies to provide a broader overview of the factors influencing students' intention to use AI tools. For example, examining students' level of trust or their privacy concerns may provide a fresh viewpoint adoption barrier. Therefore, future researchers can create a deeper and more reliable model to learn more about what motivates or deters students from using AI tools.

5.5 Conclusion

In summary, this study investigates the factors affecting Malaysian university students' intention to use AI tools, focusing on PEU, PU, SoI, and HB. The results show that PEU and HB have a significant impact on student intention, while PU and SoI have no significant impact. These results have important ramifications for politicians, organizations, and educators looking to advance AI in higher education. This study sets the foundation for future research to further examine students' intention towards AI adoption, although there are some limitations.

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Appendix

Appendix A Questionnaire

Factors Affecting Malaysian University Students' intention to use Artificial Intelligence (AI)

Dear respondents,

We are final-year students currently pursuing a Bachelor's Degree in Business Administration at the Teh Hong Piow Faculty of Business and Finance, Universiti Tunku Abdul Rahman (UTAR) Kampar Campus. We are currently working on our final year project, and the purpose of this survey is to collect data for our research titled **"The Factors Affecting Malaysian University Students' Intention to Use Artificial Intelligence (AI)."**

There are **SIX (6) sections** in this questionnaire. Section A is on demographics. Section B, C, D, E and F cover all of the variables in this study. Please read the instructions carefully before answering the questions. Please answer ALL questions in ALL sections. Completion of this questionnaire will take you approximately 10 to 15 minutes.

Your participation in this study is entirely voluntary. The information collected from you will be kept **strictly private and confidential.** All responses and findings will be used solely for academic purpose. Your assistance in completing this questionnaire is very much appreciated.

If you have any question regarding to this questionnaire, you may contact us at 012-538 6992 (Chang Ching Yee). If you decide to complete this attached anonymous questionnaire, this will be taken as you voluntarily agree and formal consent to participate in this study. Thank you very much for your cooperation and willingness to participate in this study.

Yours sincerely,
Chang Ching Yee
Lim Chai Yin
Loo Chia Yuan

* Indicates required question

PERSONAL DATA PROTECTION NOTICE

Please be informed that in accordance with Personal Data Protection Act 2010 ("PDPA") which came into force on 15 November 2013, Universiti Tunku Abdul Rahman ("UTAR") is hereby bound to make notice and require consent in relation to collection, recording, storage, usage and retention of personal information.

1. Personal data refers to any information which may directly or indirectly identify a person which could include sensitive personal data and expression of opinion. Among others it includes: Name, identity card, place of birth, address, education history, employment history, medical history, blood type, race, religion, photo, personal information and associated research data.

2. The purposes for which your personal data may be used are inclusive but not limited to:

a) For assessment of any application to UTAR
b) For processing any benefits and services
c) For communication purposes
d) For advertorial and news
e) For general administration and record purposes
f) For enhancing the value of education
g) For educational and related purposes consequential to UTAR
h) For replying any responds to complaints and enquiries
i) For the purpose of our corporate governance
j) For the purposes of conducting research/ collaboration

3. Your personal data may be transferred and/or disclosed to third party and/or UTAR collaborative partners including but not limited to the respective and appointed outsourcing agents for purpose of fulfilling our obligations to you in respect of the purposes and all such other purposes that are related to the purposes and also in providing integrated services, maintaining and storing records. Your data may be shared when required by laws and when disclosure is necessary to comply with applicable laws.

4. Any personal information retained by UTAR shall be destroyed and/or deleted in accordance with our retention policy applicable for us in the event such information is no longer required.

5. UTAR is committed in ensuring the confidentiality, protection, security and accuracy of your personal information made available to us and it has been our ongoing strict policy to ensure that your personal information is accurate, complete, not misleading and updated. UTAR would also ensure that your personal data shall not be used for political and commercial purposes.

Consent:

1. By submitting or providing your personal data to UTAR, you had consented and agreed for your personal data to be used in accordance to the terms and conditions in the Notice and our relevant policy.

2. If you do not consent or subsequently withdraw your consent to the processing and disclosure of your personal data, UTAR will not be able to fulfill our obligations or to contact you or to assist you in respect of the purposes and/or for any other purposes related to the purpose.

3. You may access and update your personal data by writing to us at

ccyee2003@1utar.my,

limchaiyin02@1utar.my, or

lcy824310@1utar.my

1. Acknowledgement of Notice *

Mark only one oval.

- I have been notified and that I hereby understood, consented and agreed per UTAR above notice.
- I disagree, my personal data will not be processed.

Section A: Demographic

This section collects general information about your background.

Please select **ONE** answer for each question that best reflects your personal information. Your responses will remain confidential and are solely for academic research purposes.

2. 1. Gender *

Mark only one oval.

- Male
- Female

3. 2. Age *

Mark only one oval.

- 18 - 20 years old
- 21 - 23 years old
- 24 - 26 years old
- > 26 years old

4. 3. Education Level *

Mark only one oval.

- Diploma
- Bachelor
- Master & PhD

5. 4. University Type *

Mark only one oval.

- Private University
- Public University

6. 5. Location of University *

Mark only one oval.

- Kuala Lumpur
- Selangor
- Perak
- Penang
- Others

7. 6. Duration of Using AI Tools. *

Mark only one oval.

- 0 year to 1 year
- More than 1 year to 2 years
- More than 2 years to 3 years
- More than 3 years

Section B: Student Intention to use AI

This section shows the statement about the **Student Intention to use AI**.

Example of AI: ChatGPT, Deepseek, Quillbot and other.

Kindly choose **ONE** of the most relevant scales to indicate your level of agreement with the following statement(s). Kindly take note of the rating scale shown below before you begin answering the question.

(1) Strongly Disagree
(2) Disagree
(3) Neutral
(4) Agree
(5) Strongly Agree

8. 1. I plan to continue using AI tools for academic or extracurricular activity. *

Mark only one oval.

	1	2	3	4	5	
Stroı	◯	◯	◯	◯	◯	Strongly Agree

9. 2. I will try to use AI tools regularly for academic or extracurricular activities. *

Mark only one oval.

	1	2	3	4	5	
Stroı	◯	◯	◯	◯	◯	Strongly Agree

10. 3. I intend to continue to use AI tools frequently for academic or extracurricular activities. *

Mark only one oval.

	1	2	3	4	5	
Stroı	◯	◯	◯	◯	◯	Strongly Agree

11. 4. I intend to be a heavy user of AI tools for academic or extracurricular activities. *

Mark only one oval.

	1	2	3	4	5	
Stroı	◯	◯	◯	◯	◯	Strongly Agree

Section C: Perceived Ease of Use

This section shows the statement about the **Perceived Ease of Use**.

Kindly choose **ONE** of the most relevant scales to indicate your level of agreement with the following statement(s). Kindly take note of the rating scale shown below before you begin answering the question.

(1) Strongly Disagree
(2) Disagree
(3) Neutral
(4) Agree
(5) Strongly Agree

12. 1.Using AI tools, academic learning or extracurricular activities become easy. *

Mark only one oval.

	1	2	3	4	5	
Stroı	◯	◯	◯	◯	◯	Strongly Agree

13. 2. Using AI tools for academic learning or extracurricular activities requires less mental effort. *

Mark only one oval.

	1	2	3	4	5	
Stroı	◯	◯	◯	◯	◯	Strongly Agree

14. 3.Academic learning or extracurricular activities are easy and understandable with AI tools. *

Mark only one oval.

	1	2	3	4	5	
Stroı	◯	◯	◯	◯	◯	Strongly Agree

15. 4. I can easily become skillful at using AI tools for academic learning or extracurricular activities. *

Mark only one oval.

	1	2	3	4	5	
Stroı	◯	◯	◯	◯	◯	Strongly Agree

16. 5. I think I will be able to learn using AI tools without the help of an expert. *

Mark only one oval.

	1	2	3	4	5	
Stroı	◯	◯	◯	◯	◯	Strongly Agree

Section D: Perceived Usefulness

This section shows the statement about the **Perceived Usefulness**.

Kindly choose **ONE** of the most relevant scales to indicate your level of agreement with the following statement(s). Kindly take note of the rating scale shown below before you begin answering the question.

(1) Strongly Disagree
(2) Disagree
(3) Neutral
(4) Agree
(5) Strongly Agree

17. 1. Using AI tools for academic learning or extracurricular activities enables me to achieve learning and extracurricular objectives effectively. *

Mark only one oval.

	1	2	3	4	5	
Stroı	◯	◯	◯	◯	◯	Strongly Agree

18. 2. Academic learning or extracurricular activities using AI tools improves my performance. *

Mark only one oval.

	1	2	3	4	5	
Stroı	◯	◯	◯	◯	◯	Strongly Agree

19. 3. Using AI tools is useful to provide access to information. *

Mark only one oval.

	1	2	3	4	5	
Stroı	◯	◯	◯	◯	◯	Strongly Agree

20. 4. Using AI tools for academic learning or extracurricular activities will increase my productivity. *

Mark only one oval.

	1	2	3	4	5	
Stroı	◯	◯	◯	◯	◯	Strongly Agree

Section E: Social Influence

This section shows the statement about the **Social Influence**.

Kindly choose **ONE** of the most relevant scales to indicate your level of agreement with the following statement(s). Kindly take note of the rating scale shown below before you begin answering the question.

(1) Strongly Disagree
(2) Disagree
(3) Neutral
(4) Agree
(5) Strongly Agree

21. 1. People who important for me think I should use AI tools. *

Mark only one oval.

	1	2	3	4	5	
Stroı	◯	◯	◯	◯	◯	Strongly Agree

22. 2. People who influence my behavior believe that I should use AI tools. *

Mark only one oval.

	1	2	3	4	5	
Stroı	◯	◯	◯	◯	◯	Strongly Agree

23. 3. People whose opinions I value prefer me to use AI tools. *

Mark only one oval.

	1	2	3	4	5	
Stroı	◯	◯	◯	◯	◯	Strongly Agree

24. 4. My friends have already adopted and are using AI tools for academic or extracurricular activities. *

Mark only one oval.

	1	2	3	4	5	
Stroı	◯	◯	◯	◯	◯	Strongly Agree

Section F: Habit

This section shows the statement about the **Habit**.

Kindly choose **ONE** of the most relevant scales to indicate your level of agreement with the following statement(s). Kindly take note of the rating scale shown below before you begin answering the question.

(1) Strongly Disagree
(2) Disagree
(3) Neutral
(4) Agree
(5) Strongly Agree

25. 1. Using AI tools to complete my task has become a habit for me. *

Mark only one oval.

	1	2	3	4	5	
Stroı	◯	◯	◯	◯	◯	Strongly Agree

26. 2. An AI tools will be my first option whether an enquiry or seek information regarding academic or extracurricular matters. *

Mark only one oval.

	1	2	3	4	5	
Stroı	◯	◯	◯	◯	◯	Strongly Agree

27. 3. I feel comfortable using AI tools to look for a solution regarding academic or extracurricular matters. *

Mark only one oval.

	1	2	3	4	5	
Stroı	◯	◯	◯	◯	◯	Strongly Agree

28. 4. Using an AI tools is something I do without hesitation. *

Mark only one oval.

	1	2	3	4	5	
Stroı	◯	◯	◯	◯	◯	Strongly Agree

Thank You For Your Participation !

Your respond is crucial to our research, and I am grateful for you thoughtful contributions. Thank you once again for taking the time to participate in our survey! Your dedication to advancing knowledge is greatly appreciated.

Appendix B- SPSS Result from Pilot study

Scale: Reliability Analysis for Student Intention

Case Processing Summary

		N	%
Cases	Valid	30	100.0
	Excluded[a]	0	.0
	Total	30	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.823	.831	4

Scale: Reliability Analysis for Perceived Ease of Use

Case Processing Summary

		N	%
Cases	Valid	30	100.0
	Excluded[a]	0	.0
	Total	30	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.760	.802	5

Scale: Reliability Analysis for Perceived Usefulness

Case Processing Summary

		N	%
Cases	Valid	30	100.0
	Excluded[a]	0	.0
	Total	30	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.815	.815	4

Scale: Reliability Analysis for Social Influence

Case Processing Summary

		N	%
Cases	Valid	30	100.0
	Excluded[a]	0	.0
	Total	30	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.912	.912	4

Scale: Reliability Analysis for Habit

Case Processing Summary

		N	%
Cases	Valid	30	100.0
	Excluded[a]	0	.0
	Total	30	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.777	.793	4

Appendix C- SPSS Result from Full study

Frequency Table

Gender

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Male	189	49.2	49.2	49.2
	Female	195	50.8	50.8	100.0
	Total	384	100.0	100.0	

Age

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	18 to 20 years old	124	32.3	32.3	32.3
	21 to 23 years old	164	42.7	42.7	75.0
	24 to 26 years old	80	20.8	20.8	95.8
	more than 26 years old	16	4.2	4.2	100.0
	Total	384	100.0	100.0	

Education Level

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Diploma	138	35.9	35.9	35.9
	Bachelor	222	57.8	57.8	93.8
	Master & PhD	24	6.2	6.2	100.0
	Total	384	100.0	100.0	

University Type

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Private University	192	50.0	50.0	50.0
	Public University	192	50.0	50.0	100.0
	Total	384	100.0	100.0	

Location of University

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Kuala Lumpur	74	19.3	19.3	19.3
	Selangor	56	14.6	14.6	33.9
	Perak	102	26.6	26.6	60.4
	Penang	71	18.5	18.5	78.9
	Others	81	21.1	21.1	100.0
	Total	384	100.0	100.0	

Duration of using AI tools

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	0 year to 1 year	43	11.2	11.2	11.2
	More than 1 year to 2 years	160	41.7	41.7	52.9
	More than 2 years to 3 years	88	22.9	22.9	75.8
	More than 3 years	93	24.2	24.2	100.0
	Total	384	100.0	100.0	

Frequencies

[DataSet0]

Statistics

		Student Intention Average	Perceived Ease of Use Average	Perceived Usefulness Average	Social Influence Average	Habit Average
N	Valid	384	384	384	384	384
	Missing	0	0	0	0	0
	Mean	4.3698	4.4698	4.5645	4.5000	4.4167
	Std. Deviation	.49141	.50203	.48399	.57782	.56862

Descriptives

[DataSet0]

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
Student Intention Average	384	2.00	5.00	4.3698	.49141	-.576	.125	1.305	.248
Perceived Ease of Use Average	384	2.40	5.00	4.4698	.50203	-.643	.125	.217	.248
Perceived Usefulness Average	384	2.50	5.00	4.5645	.48399	-.854	.125	.395	.248
Social Influence Average	384	1.00	5.00	4.5000	.57782	-1.467	.125	4.065	.248
Habit Average	384	1.75	5.00	4.4167	.56862	-1.089	.125	2.117	.248
Valid N (listwise)	384								

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	1.436	.235		6.109	.000		
	Perceived Ease of Use Average	.384	.049	.393	7.829	.000	.713	1.403
	Perceived Usefulness Average	.068	.052	.067	1.306	.192	.679	1.472
	Social Influence Average	.033	.046	.039	.720	.472	.600	1.668
	Habit Average	.171	.045	.198	3.821	.000	.669	1.494

a. Dependent Variable: Student Intention Average

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
Student Intention Average	Equal variances assumed	.036	.850	.104	382	.917	.00521	.05022	-.09353	.10395
	Equal variances not assumed			.104	379.511	.917	.00521	.05022	-.09354	.10395

Scale: Reliability Analysis for Student Intention

Case Processing Summary

		N	%
Cases	Valid	384	100.0
	Excluded[a]	0	.0
	Total	384	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.876	.877	4

Scale: Reliability Analysis for Perceived Ease of Use

Case Processing Summary

		N	%
Cases	Valid	384	100.0
	Excluded[a]	0	.0
	Total	384	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.908	.910	5

Scale: Reliability Analysis for Perceived Usefulness

Case Processing Summary

		N	%
Cases	Valid	384	100.0
	Excluded[a]	0	.0
	Total	384	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.895	.896	4

Scale: Reliability Analysis for Social Influence

Case Processing Summary

		N	%
Cases	Valid	384	100.0
	Excluded[a]	0	.0
	Total	384	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.923	.923	4

Scale: Reliability Analysis for Habit

Case Processing Summary

		N	%
Cases	Valid	384	100.0
	Excluded[a]	0	.0
	Total	384	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.881	.881	4

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.567[a]	.321	.314	.40705

a. Predictors: (Constant), Habit Average, Perceived Ease of Use Average, Perceived Usefulness Average, Social Influence Average

b. Dependent Variable: Student Intention Average

ANOVA[b]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	29.692	4	7.423	44.800	.000[a]
	Residual	62.798	379	.166		
	Total	92.490	383			

a. Predictors: (Constant), Habit Average, Perceived Ease of Use Average, Perceived Usefulness Average, Social Influence Average

b. Dependent Variable: Student Intention Average

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.436	.235		6.109	.000
	Perceived Ease of Use Average	.384	.049	.393	7.829	.000
	Perceived Usefulness Average	.068	.052	.067	1.306	.192
	Social Influence Average	.033	.046	.039	.720	.472
	Habit Average	.171	.045	.198	3.821	.000

a. Dependent Variable: Student Intention Average

Appendix D – Original Questionnaire Items

Section B: Dependent Variable

Variable	Original Questionnaire	Source
Student Intention to use AI	1. I plan to continue using AI_Art for making advertisements 2. I will try to use AI_Art regularly for making advertisements 3. I intend to continue to use AI_Art frequently for advertising. 4. I intend to be a heavy user of e-learning system	Maican et al. (2023) and Park (2009)

Section C, D, E, F: Independent Variables

Variable	Original Questionnaire	Source
Perceived ease of use	1. Using ChatGPT, learning becomes easy. 2. Using ChatGPT for learning requires less mental effort. 3. Learning is easy and understandable with ChatGPT 4. I can easily become skillful at using ChatGPT for learning 5. I think I will be able to learn using ChatGPT without the help of an expert.	Rahman et al. (2023)
Perceived usefulness	1. Using ChatGPT for learning enables me to achieve learning objectives effectively. 2. Learning from ChatGPT improves my performance 3. Using ChatGPT is useful to provide access to information 4. Using ChatGPT for learning will increase my productivity.	Rahman et al. (2023)
Social influence	1. People who important for me think I should use ChatGPT 2. People who influence my behavior believe that I should use ChatGPT	Changalima et al. (2024) and Kim et al. (2024)

	3. People whose opinions I value prefer me to use ChatGPT. 4. Competitors have already adopted and are using generative AI systems.	
Habit	1. Using AI_Art to make ads has become a habit for me. 2. A chatbot will be my first option whether an enquiry or seek information regarding academic matters 3. I feel comfortable using a chatbot to look for a solution regarding academic matters 4. Using a chatbot is something I do without thinking	Maican et al. (2023) and Rahim et al. (2022)