STUDENT MOTIVATION AND AI USE: A PATHWAY TO PERCEIVED ACADEMIC PERFORMANCE

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DECLARATION

We hereby declare that:

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

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

(3) The word count of this research report is 20299.

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DEDICATION

I would like to dedicate this thesis to my beloved family, who never let me face anything alone, who stood behind me through every challenge. Their encouragement has been the greatest fuel for my ambition.

To my supervisor, Mr. Low Choon Wei, thank you for always being supportive and for providing guidance and insightful feedback I needed to keep moving forward. You have assisted me in every stage of this research. Without your mentorship, it would be a huge challenge for me to complete my final year project.

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LIST OF ABBREVIATION

AI	Artificial Intelligence
SDT	Self-Determination Theory
TAM	Technology Acceptance Model
AUT	Autonomy
REL	Relatedness
COM	Competence
PEOU	Perceived Ease of Use
PU	Perceived Usefulness
BIU	Behavioural Intention to Use AI
AIU	AI Usage
AP	Perceived Academic Performance
FAM	Faculty of Accountancy and Management
SPSS	Statistical Package for the Social Sciences
CA	Cronbach's Alpha
VIF	Variance Inflation Factor
β	Path Coefficient
R^2	Coefficient of Determination
α	Alpha
r	Correlation Coefficient

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PREFACE

This research emerged from the author’s growing curiosity about the rapid integration of artificial intelligence in university learning environments and the ways students adapt to these technological changes. Over time, AI tools have become increasingly common among students, functioning not only as study aids but also as support for research, writing, and problem-solving. As the author observed how differently students engaged with these tools—some adopting them with confidence, others with hesitation—it became clear that motivation plays a meaningful role in shaping their behaviour.

The idea for this study developed as the author noticed a recurring question among peers: why do some students use AI regularly and comfortably, while others remain uncertain or reluctant? This question aligned with the author’s academic interest in behavioural factors and technology adoption, which guided the decision to explore the topic using the Self-Determination Theory and the Technology Acceptance Model.

This research was also inspired by the need to understand how AI usage influences students’ perceived academic performance. As AI technology continues to advance, universities must not only invest in digital infrastructure but also understand students’ readiness, experiences, and challenges. By applying a mixed-methods approach, the author aimed to capture both measurable patterns and authentic student perspectives.

The author hopes that the insights from this research contribute to a deeper understanding of how motivation, technological perceptions, and educational needs intersect in shaping the future of learning. It is also hoped that this work will support educators, policymakers, and students in navigating the evolving role of AI in higher education.

ABSTRACT

The rapid advancement of artificial intelligence has now changing the way people learn in university around the world. It offers new opportunities for personalised learning, improved efficiency and enhanced academic support. However, despite Malaysia's national initiatives to strengthen digital readiness, the adoption of AI tools among university students remains uneven. This study examines the motivational factors that influence Malaysian university students' intention to use AI, investigates how AI usage relates to their perceived academic performance and identifies key challenges they faced while using AI.

This study grounded in the Self-Determination Theory (SDT) and the Technology Acceptance Model (TAM), this research explores both intrinsic and extrinsic drivers of AI usage. SDT highlights the importance of autonomy, relatedness and competence, whereas TAM mentioned about perceived usefulness and ease of use as determinants of behavioural intention to use AI. By integrating both frameworks, this study provides comprehensive understanding of students' readiness in adopting AI in higher education.

This study also applied mixed-method design which incorporating both quantitative surveys and qualitative interviews to capture students' AI experience. The findings revealed that competence, relatedness and perceived usefulness are the strong predictor of behavioural intention to use AI. AI usage was also found to have a positive relationship with perceived academic performance. Nonetheless, there are few challenges emerged, including insufficient trust in AI, privacy concerns, over-reliance, etc.

CHAPTER 1: INTRODUCTION

1.0 Introduction

In the contemporary era, technology has had a profound impact on every aspect of human life, with such effects being especially notable in the field of education. In the previous era, artificial intelligence began with rule-based systems, where logic and pre-defined rules constituted the fundamental framework for intelligence. These early systems were highly specialised and could only perform specific tasks, such as ELIZA and Logic Theorists (Radanliev, 2024). Nowadays, the scope of artificial intelligence has expanded from these niche applications to wider large language models such as Generative Pretrained Transformer, Claude, Gemini, Perplexity AI, etc. These large language models possess abilities to perform various tasks across different aspects, including education, healthcare, and other key industries.

In the educational context, higher institutions and students have applied artificial intelligence to their academic tasks. Annamalai et al. (2023) observed that students have widely used artificial intelligence tools for writing assistance, research and class assignments. Moreover, students using artificial intelligence tools for English language learning experience improvements in various language skills like listening, speaking, reading, writing, and vocabulary. These artificial intelligence tools deliver immediate feedback to students, allowing students to personalise their own learning pace.

1.1 Research Background

The rapid revolution of technology, especially AI is reshaping the landscape of higher education. With technology advancements such as artificial intelligence, automation, and big data analytics becoming progressively integrated into higher education, students can enrich their learning experience by personalising their learning pace, fostering greater engagement, and improving overall academic performance.

However, even though AI tools have huge potential to improve learning styles, their adoption and integration in higher education are still relatively low. This gap can often link to psychological factors, such as what motivated students to use AI and how they perceive their usefulness and ease of use. In order to have an in depth understanding on these factors, there are two key theoretical frameworks: Self-Determination Theory (SDT) and Technology Acceptance Model (TAM). According to TAM, students' intention to use AI largely depends on how easy they think the tools are to use and how useful they believe these tools will be for their academic tasks. Furthermore, SDT highlights the importance of intrinsic motivation, where students feel a sense of autonomy, competence, and relatedness influence their willingness to interact with AI technologies.

In Malaysia, the government has launched initiatives like the Malaysia Education Blueprint (Higher Education) 2015-2025 and Industry 4.0 programmes to modernise and keep up the pace with global technological trends. Nonetheless, the AI adoption among Malaysian universities is still unbalanced. Consequently, students frequently lack readiness for the skills demanded by employers, especially in technology driven positions.

This study aims to fill that gap by looking at how students' motivation guided by SDT and TAM, influence their behavioural intention to use AI and actual usage of these AI tools. The research will also examine how AI usage affects academic performance and identifies the challenges students face in adopting AI. In contrast to previous studies that relied solely on quantitative methods, this study will apply both quantitative and qualitative approaches to provide more thorough insight into the matter.

1.2 Problem Statements

Malaysian universities are facing a critical challenge in preparing students with the skills required to fulfil the evolving demand of the job market, particularly in high-growth sectors such as artificial intelligence, renewable energy, and digital technologies. Meanwhile, traditional industries like manufacturing and clerical work see a decline in demand. Although numerous government initiatives and industry-academia collaboration, employers continued reporting that university graduates often lack the necessary skills and competencies to thrive in an increasingly dynamic job landscape. This ongoing disparity in skills not only impacts the employability of graduates but also hinders the country's attempts to develop a knowledge-based economy.

While AI has the potential to revolutionise education by enhancing learning personalisation, administrative efficiency, and career readiness, its integration into Malaysian higher education is still at a nascent stage. Major obstacles to AI adoption include a limited awareness of AI's potential, inadequate infrastructure, and concerns over data privacy and equity. Furthermore, students encounter issues like insufficient trust in AI, privacy breaches, over-reliance on AI and lack of confidence in using AI (Khairuddin et al., 2024). These obstacles lead to a disconnect in digital literacy within higher education, hindering students from acquiring the competencies essential for success in today's job market.

On the other hand, there is insufficient comprehension about the motivational elements that affect Malaysian university students' readiness to engage with AI tools in their educational experience. This lack of understanding obstructs the effective design and implementation of AI driven educational solutions tailored to students’ needs and aspirations.

1.3 Research Questions

1) What are the key factors influencing university students’ willingness to use artificial intelligence tools?
2) What is the relationship between usage of artificial intelligence and perceived academic performance?
3) What are the challenges in AI adoption in higher education?

1.4 Research Objectives

1.4.1 General Objective

The general objective of this study is to explore the factors that influence Malaysian university students’ motivation to use AI and to determine how AI usage affect their perceived academic performance.

1.4.2 Specific Objectives

1) To determine the key factors that influence university students’ willingness to use artificial intelligence tools.

2) To analyse the relationship between university students' usage of artificial intelligence tools and their perceived academic performance.
3) To identify the challenges in AI adoption.

1.5 Significance of Study

The study holds significant implications for stakeholders in higher education, involving policymakers, educators, students and employers. It provides insight into what drives students to use AI tools and how this impact their academic performance, assisting universities in making informed decisions regarding the incorporation of AI in education. The findings will inform policy development, guide institutional strategies, and support the creation of an education ecosystem that is both inclusive and future ready.

For policymakers, the study provides useful data to support national education reforms and to ensure that AI adoption is aligned with the country's long-term development goals. For educators, the study highlights how AI tools can be woven into the educational journey to improve teaching efficacy, encourage student engagement, and facilitate more tailored learning experiences that match students' specific requirements.

For students, the research may enhance students' awareness on how AI tools can support their education, improve their academic progress and equip them for future professions, specifically in technology sector. For employers, the findings help to address the talent gap and foster the growth of graduates with the skills needed to succeed in AI-driven workplace.

1.6 Outline of the Study

This study is organised into 5 (five) chapters:

Chapter 1: Introduction

This chapter introduces the study by outlining the research background, problem statement, research questions, research objectives, hypothesis, significance of study and overall framework of the research.

Chapter 2: Literature Review

This chapter reviews relevant theories and previous research related to AI adoption, students' motivation to use AI, Self-Determination Theory (SDT), Technology Acceptance Model (TAM), academic performance, and opportunities and challenges in AI adoption. It also reveals research gaps and shows the conceptual framework of the study.

Chapter 3: Methodology

This chapter explains the research design, targeted participants, population and sampling methods, data collection approaches, measurement tools, and data analysis techniques applied in this study.

Chapter 4: Data Analysis

This chapter presents the findings from the data analysis, including descriptive statistics, reliability tests, validity assessments and hypotheses tests relevant to the study.

Chapter 5: Conclusion and Implication

This chapter summarises the main findings, explores theoretical and practical implications, provide recommendations for future study and concludes the study.

CHAPTER 2: LITERATURE REVIEW

2.0 Introduction

Chapter 2 gives an overview of the applied theories, ideas, and empirical research that support this study. This chapter aims to situate the study within the context of existing scholarly discussions and highlight the research gaps.

2.1 Reviews of Relevant Theoretical Models

2.1.1 Self-Determination Theory (SDT)

Motivation has historically been perceived as a one-dimensional concept—whether individuals are motivated or not. Early psychological theories, including behaviourism and drive theories, viewed motivation mainly in terms of external rewards and reinforcements. However, the complexity of human motivation could not be fully explained by these perspectives alone (Ryan & Deci, 2000).

As Ryan and Deci (1985) developed Self-Determination Theory (SDT), pointed out that motivation involves not only the amount (how much motivation) but also a matter of quality (what kind of motivation). SDT provides a broad framework for comprehending human motivation. This theory suggests that people possess three core psychological needs: *autonomy, competence*, and *relatedness*. In educational contexts, SDT has transformed the comprehension of how motivation affects academic achievement, engagement, and psychological well-being. Rather than focusing solely on grades or external incentives, SDT highlights the importance of creating learning settings that support students' psychological needs. When students fulfil these three psychological needs, they tend to improve their academic performance and emotional health.

Autonomy is an individual's inherent psychological requirement to be the driving force behind their own life and to act in alignment with their cohesive self. In other words, one should act in a way that aligns with one's true self and participate in activities not because of obligation or duty (e.g., due to social pressure, norms, or to appear good), but instead voluntarily because one has the right and freedom to do so (Deci, 1995, as cited in Karahanna et al., 2018). When individuals feel autonomous, they view their behaviours as self-supporting, voluntarily selected and indicative of personal control.

In recent years, many studies have broadened the application of SDT to investigate the motivation behind the technology used due to the rapid technological advancements, especially in artificial intelligence sector. In this context, autonomy refers to the individual's ability to make choices and act independently, without external forces (Deci et al., 2017; Lai et al., 2023). AI tools such as ChatGPT foster autonomy because they are accessible anytime and anywhere, free from time and location constraints (Masrek et al., 2024). This flexibility empowers learners to use AI in their academically seamlessly, thereby allowing them to self-direct their learning process based on their own pace and choices (Lai et al., 2023). As Annamalai et al. (2023) suggested that AI tools enable students to take control of their educational experience by deciding what information they require, when to access it, and the extent to which they wish to explore a subject. Chatbot-based AI further boost autonomy by giving learning assistance whenever needed, enabling students to tailor their study routines and engage with content beyond the limitations of traditional classroom settings.

Competence refers to a person's intrinsic desire to feel efficient, skilled, and assured in achieving expected goals. It reflects a sense of mastery that arises when a person perceives themselves as skilled and capable of overcoming challenges effectively. According to Ryan and Deci (2020), in the environments that give optimal challenges, structured guidance, constructive feedback, and chances for growth best fulfil the need for competence. Ryan and Deci (2000) also stated that competence is not about skill level but rather about feeling confident and effective in one's action. Meeting this need has been demonstrated to have a positive correlation across different settings, including education (Benware & Deci, 1984).

In learning context, competence manifests when students perceive themselves as able to finish assignments, understanding new concepts and perform well academically (Graham & Vaughan, 2022). Nowadays, AI tools have progressively been acknowledged for their capacity to improve students' perceived competence. These resources can build up efficiency in data analysis, scientific writing, problem-based learning and critical thinking, thereby reinforcing their confidence (Avello-Sáez & Estrada-Palavecino, 2023). For example, Annamalai et al. (2023) noted that ChatGPT helps students improve their English proficiency by providing immediate corrections for spelling, punctuation, and pronunciation. This prompt feedback allows students to recognise their weaknesses and refine their skills, leading to stronger sense of competence.

Finally, *relatedness* refers the sense of belonging and connection with others, cultivated through expressions of respect and care (Ryan & Deci, 2020). This need is integral to human motivation as it affects how people interact in social environments and connections. Deci and Ryan (2000) highlighted that individuals are naturally driven to create and sustain connections where they experience care and appreciation. This need for connection also significantly influences social media usage, as the capacity to engage with others satisfies the need for relatedness (Karahanna et al., 2018).

In technology-driven educational settings, the use of AI tools can also promote relatedness. According to Annamalai, Ab Rashid, et al. (2023), AI chatbots can mimic human-like dialogue patterns, encouraging engagement and a sense of belonging among students. Other than that, Essel et al. (2024) pointed out that ChatGPT sustains conversations through follow-up questions, creating personalised learning experiences. These features show that chatbots are a tool that gives students the opportunity to interact with one another, especially because they can use natural language to communicate.

Collectively, these findings suggest that SDT provides a strong framework for understanding what factors motivate students to use AI. In this study, we apply SDT as a framework to explain how university students' psychological needs affect their willingness to use AI tools for educational purposes. SDT suggests that *autonomy*, *competence* and *relatedness* are fundamental drivers of intrinsic motivation, and when these needs are fulfilled, individuals are more likely to participate in a behaviour willingly and consistently. Applying this theory, the study suggests that students who enjoyed increased autonomy, competence and relatedness will be more intrinsically driven to adopt AI. These psychological needs are incorporated into the conceptual framework as factors influencing students' behavioural intention to use AI.

2.1.2 Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM) is applied in numerous research studies to assess users' acceptance of AI technologies. TAM specifies the causal relationships among system design features, perceived usefulness, perceived ease of use, attitude toward using and actual usage behaviour. It describes how and why individuals and organisations accept and use technology (Davis, 1989;

Venkatesh & Davis, 2000). *Perceived usefulness* is defined as the extent to which a user thinks a technology will improve his or her job effectiveness, while *perceived ease of use* refers to how little effort is required to use technology (Davis, 1989).

Many researchers have strengthened the TAM by including context-specific variables. According to Pillai and Sivathanu (2020), perceived ease of use was the strongest predictor of chatbot adoption intention, followed by perceived usefulness, perceived trust, perceived intelligence, and anthropomorphism. Moreover, the study highlighted that perceived usefulness and perceived ease of use have 40% of explanatory power to describe the reasons for using technology. Other than that, study also indicated that students' adoption intention directly affects their actual usage in AI (Pillai et al., 2023). Similarly, Erdmann and Toro-Dupouy (2025) stated that perceived ease of use and perceived usefulness are important drivers of willingness to use AI in universities. Shao et al. (2024) reinforced these findings by revealing that "effort expectancy (which is conceptually similar to perceived ease of use) has a positive effect on user attitudes toward AI adoption in higher education". Multiple studies have applied TAM to explore the impact and use of AI technologies in online learning (Choi et al., 2023; Kim et al., 2020), emphasising the crucial role of perceived usefulness and ease of communication in influencing the AI-enabled technologies' final adoption. Overall, these studies suggest that TAM is a robust framework for understanding the factors influencing users' acceptance of AI.

However, several recent studies argue that TAM is insufficient for examining the usage and adoption of AI technologies. While TAM concentrates on two main factors: perceived usefulness and perceived ease of use, it ignores context-specific factors that have a huge impact on user acceptance, such as social norms, cognitive absorption and previous experience (Lu et al., 2019). Furthermore, Kelly et al. (2023) underscored that the TAM is limited in its ability to comprehend the complexities of AI acceptance because it mainly assesses actual behaviour as an outcome variable. Together, both studies highlight the limitations of TAM in examining users' acceptance of AI adoption.

Together, these findings suggest that TAM has both pros and cons in understanding how students are motivated to use AI. In this study, we employs TAM to investigate how students' perceived usefulness and perceived ease of use affect the intention to use AI. When they think AI is user-friendly and useful in assisting them to reach educational goals, they will intend to use it.

2.2 Empirical Reviews of the Study

2.2.1 The Relationship between Autonomy and Behavioural Intention to Use AI

According to the empirical findings conducted by Surachmi et al. (2025), it found that autonomy is significantly predicted students' behavioural intention to use AI for English learning. Students who believed that AI tools enabled them to learn independently and make their own decisions were more motivated to use them. Similarly, Yang (2024) discovered that autonomy-related intrinsic motivations impacted students' perceptions of a technology used, which in turn influenced their intention. Furthermore, Alharbi (2023) further support this statement in MOOC context. The researcher studied MOOC implementation in health informatics training. Although MOOCs are not AI systems, they serve as online educational technologies that require learners to take charge for their own studies. This research indicated that when students felt empowered and in charge of their learning decisions, they show greater intention to participate in MOOCs. Moreover, Cortez et al. (2024) also proved that autonomy significantly influenced the intention to use AI. Together, these studies have suggested that autonomy is a strong predictor of behavioural intention to use AI.

2.2.2 The Relationship between Relatedness and Behavioural Intention to Use AI

According to Surachmi et al. (2025), relatedness significantly forecasted students' behavioural intention to use AI for learning English. Students who believed that AI tools offered interactive or socially engaging experiences tend to use them. Additionally, Alharbi (2023) showed that relatedness is notably predicted behavioural intention to use MOOCs. Students who perceived support and connection, whether via instructor involvement, peer networks, or platform interaction, were continued using online learning platform. Other than that, Wong and Tajudeen (2025) found that relatedness enhanced users' perceptions of the Metaverse platform (a digital environment), subsequently affecting their intention to engage behaviourally. Although relatedness did not directly forecast intention in this study, having a sense of social support in the tech environment increased users' willingness to adopt AI. Jointly, these studies have suggested that relatedness is a strong predictor of behavioural intention to use AI.

2.2.3 The Relationship between Competence and Behavioural Intention to Use AI

According to Alharbi (2023), competence had direct impact on the intention to use MOOCs. This indicates that when students perceive themselves as technically or academically proficient, they are more likely to use online learning platform. However, the study conducted by Surachmi et al. (2025), reported that competence did not significantly impact intention to use AI. This difference can be explained by the nature of technology discussed in articles, as MOOCs require a more structured and content-focused competence, while AI tools provide more adaptable and personalised learning opportunities. In this case, students may not need to immediately view themselves as competent in the tools. Since AI tools like ChatGPT provide personalised learning, they could facilitate intention to use even when students don't feel "competent" in using them. Other than that, these studies were conducted in different cultural and educational settings, this could also impact the findings of them

Figure 2.1

Conceptual Framework of the Relationship Between SDT and Behavioural Intention to Use AI

Adapted from: Surachmi, S. W., Solihati, T. A., Rahmatika, L., Musdalifah, Islam, M. M., & Haryanto, S. (2025). Understanding EFL Students' Adoption of Generative AI for English Learning: An Integrated UTAUT2 Model and Self-Determination Theory, Online Learning, *29(4), 311-340.*

2.2.4 The Relationship between Perceived Usefulness and Behavioural Intention to Use AI

According to Liu et al. (2024), perceived usefulness is significantly influences users' behavioural intention to use AI-driven autonomous taxis. Similarly, Manolică et al. (2025), in their study on AI in Digital Marketing, mentioned that Gen Z, who demonstrated greater familiarity of AI tools, exhibit a strong intention to use AI when they perceived it as useful for their everyday tasks and activities. This match with Davis (1989) initial statement in the TAM, where perceived usefulness is directly related to usage intentions. Furthermore, study also examined how university students adopted ChatGPT, finding that perceived usefulness significantly influenced students' intention to use ChatGPT for their academic needs (Duong et al., 2023). Other than that, Esiyok et al. (2024) discovered that students who felt that chatbots were helpful for giving immediate assistance were more likely have strong intention to use them. This finding is further supported by Hussain et al. (2025), indicated that the intention of healthcare workers to adopt advanced medical technologies was strongly impacted by their perception of the system's usefulness in improving patient care and optimising workflow. Together, these studies proved that perceived usefulness can affect the intention to use AI.

2.2.5 The Relationship between Perceived Ease of Use and Behavioural Intention to Use AI

In study conducted by Duong et al. (2023), it found that perceived ease of use is significantly influence students' intention to use ChatGPT for learning. Students who think that ChatGPT is user-friendly were more likely to intend to use AI for their academic tasks. The research highlighted that a perception of minimal effort for using the AI tool will encourage a greater intention to use it consistently. This finding matches with Davis (1989) initial claim, saying that when users view technology as user-friendly, easy to use, they will tend to engage with it. In healthcare context, Hussain et al. (2025) mentioned that nurses' perspectives on the user-friendly advanced medical technologies were significantly linked to their willingness to adopt these tools. This study indicated that nurses' intention to use medical AI systems into their daily clinical practice increased when they perceived these systems as comprehensible. Similarly, Manolică et al. (2025) also supported that perceived ease of use positively affected Gen Z's intention to use AI tools. Esiyok et al. (2024) stated that students' perceptions of ease of use was a strong predictor of behavioural intention to use AI. Collectively, these studies proved that perceived ease of use can affect the intention to use AI.

2.2.6 The Relationship between Behavioural Intention to Use AI and AI Usage

Behavioural intention refers to a person's internal attitudes or beliefs prior to participating in a specific action. This factor can determine if a person will participate in the behaviour (Fishbein et al., 1977). According to Duong et al. (2023), the intention to use ChatGPT significantly predicted actual AI usage. Meaning that higher intention to use AI will directly lead to higher actual usage of AI for academic tasks like essay writing and problem-solving. Similarly, Esiyok et al. (2024) found that the intention to use AI chatbots was strongly related to actual usage. The results indicated that students planning to use AI chatbots for personalised learning and immediate feedback were tend to interact with technologies more frequently. Additionally, Sitanaya et al. (2024) studied the implementation of ChatGPT in Jakarta's universities and highlighted a strong correlation between students' intention to us ChatGPT as a learning source and their actual usage. Furthermore, Tandon et al. (2024) investigated the AI adoption in medical training, and they found a similar finding. Their study showed that the intention to use AI tools like diagnostic assistants, was a direct predictor of their actual usage. Across all these studies, whether is in healthcare or education context, intention to use AI was a consistent predictor of AI usage.

2.2.7 The Relationship between AI Usage and Academic Performance

The increasing AI adoption in educational setting has shown a potential in improving academic performance. Dahri et al. (2025) examined the impact of ChatGPT on students' academic performance in a mobile learning environment. This research included two student groups: one experimental group using ChatGPT for post-lesson evaluations and a control group using traditional method. The findings found that the experimental group has a great improvement in academic performance compared to the control group. This discussion can be supported by Lee et al. (2022), it stated that students who used AI chatbot for after-class reviews in public health curriculum has significantly led to higher academic achievement. Another study conducted by Khalkho et al. (2024), AI tools were discovered to affect students' study habits and academic performance. It showed that the use of AI tools could assist students in understanding challenging topics. Jointly, these findings indicate that AI tools can improve academic performance.

2.2.8 Opportunities and Challenges in AI Adoption

Imran et al. (2025) compared AI personalised learning with traditional methods in Pakistan Universities and found that AI improves academic performance by tailoring resources and activities to match each student's learning style. Vincent-Lancrin et al. (2020) highlighted that AI's ability to analyse learning patterns and preferences to provide customised support. Ilkley and Rajamohan (2024) extended this discussion by showing how AI accelerates personalised learning in the classroom, especially for students with special needs. AI efficiency is not limited to personalisation. Arkün-Kocadere and Özhan (2024) found comparable performance outcomes and engagement levels between AI-generated lectures and human instructors, while noting that AI-generated lectures are more efficient and cost effective. Leong (2024) studied AI's role in supporting inclusive education in underprivileged schools, where it alleviates teacher shortages by providing alternative instructional support.

However, some researchers argue that while AI might result in long-term cost-savings, the initial investment is a major barrier for institutions with tight budgets. Mutisya and Makokha (2016), and Yılmaz (2024) identified challenges such as financial constraints, lack of infrastructure, data privacy concerns, heavy workloads, and limited ICT skills impede the adoption of e-learning in public universities. Ethical concerns arise regarding data privacy; Zhai et al. (2024) stressed the importance of robust privacy protection measures to prevent unintended disclosure of personal information. Moreover, Chatterjee and Bhattacharjee (2020) emphasised the need for greater awareness among stakeholders about the AI's benefits, as misconceptions can hinder adoption. These studies show both the potential and obstacles of AI in education, ranging from financial limitations to ethical considerations that must be addressed for successful integration.

2.3 Hypotheses Development

Hypotheses 1:

H_0: There is no relationship between autonomy (AUT) and behavioural intention to use AI (BIU)

H_A: There is a relationship between autonomy (AUT) and behavioural intention to use AI (BIU)

Hypotheses 2:

H_0: There is no relationship between competence (COM) and behavioural intention to use AI (BIU)

H_A: There is a relationship between competence (COM) and behavioural intention to use AI (BIU)

Hypotheses 3:

H_0: There is no relationship between relatedness (REL) and behavioural intention to use AI (BIU)

H_A: There is a relationship between relatedness (REL) and behavioural intention to use AI (BIU)

Hypotheses 4:

H_0: There is no relationship between perceived usefulness (PU) and behavioural intention to use AI (BIU)

H_A: There is a relationship between perceived usefulness (PU) and behavioural intention to use AI (BIU)

Hypotheses 5:

H_0: There is no relationship between perceived ease of use (PEOU) and behavioural intention to use AI (BIU)

H_A: There is a relationship between perceived ease of use (PEOU) and behavioural intention to use AI (BIU)

Hypotheses 6:

H_0: There is no relationship between behavioural intention to use AI (BIU) and AI usage (AIU)

H_A: There is a relationship between behavioural intention to use AI (BIU) and AI usage (AIU)

Hypotheses 7:

H_0: There is no relationship between AI usage (AIU) and perceived academic performance (AP)

H_A: There is a relationship between AI usage (AIU) and perceived academic performance (AP)

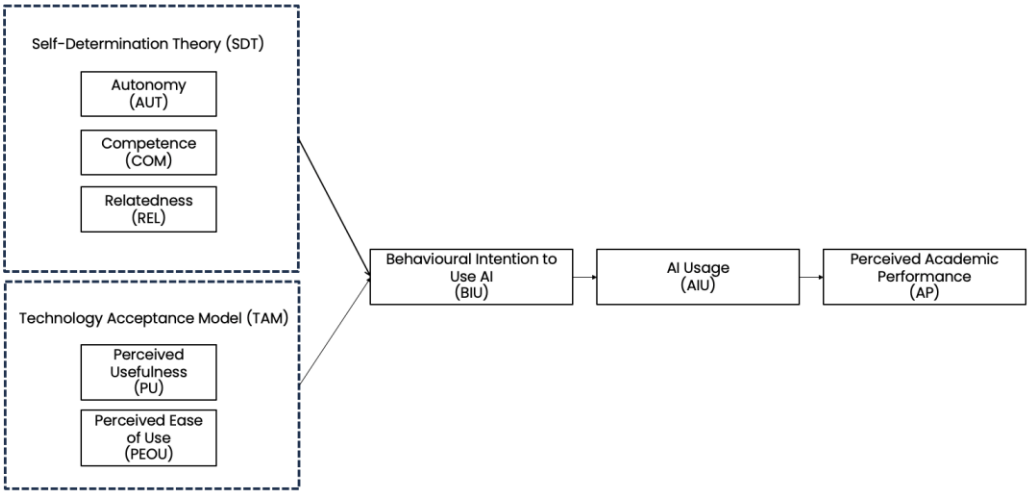
2.4 Gaps in Literatures

There are many researchers studied about the factors that motivate people to use AI by assigning SDT and TAM frameworks. But most studies are only focused on the initial of AI adoption, rather than researching its continuous use over time. This creates a gap in understanding the long-term motivations and obstacles that affect ongoing AI involvement. Other than that, most of the empirical findings are using on either quantitative or qualitative method alone, which may not sufficiently capture a comprehensive information from the participants. Moreover, there are lack of research conducted within Malaysian universities context, this may cause the educators, students, policymakers, AI developers failed to efficiently adopt AI in higher education. Consequently, this gap could slow down the country's development toward achieving its long-term goals as students are failed to equip with relevant digital skills necessary in this technology-driven world.

2.5 Proposed Conceptual Framework

The proposed conceptual framework in ***Figure 2***, is supported by the literature reviewed in Sections 2.1 and 2.2. There are five variables that motivate Malaysian university students' intention to use AI. Moreover, this framework also uses to examine how intention to use AI will influence AI usage and therefore, impact their perceived academic performance.

Figure 2.2: Proposed Conceptual Framework



Source: Author's Own Elaboration

2.6 Conclusion

Chapter 2 provides an overview of the theories and research that support this study, tt explores how the elements in SDT and TAM influence students' motivation to use AI tools. SDT highlights when students' feel increased autonomy, relatedness and competence, they will increase their engagement in AI. Conversely, TAM emphasises that the perceived usefulness and perceived ease of use are the major factors encouraging students to use AI.

Despite these important frameworks and substantial studies are conducted, a considerable gap in the literature still exists, especially concerning long-term AI implementation in higher education, continuous usage and the impact on student learning over time. These gaps may hinder Malaysia's advancement in equipping students with necessary related skills for success.

CHAPTER 3: METHODOLOGY

3.0 Introduction

This chapter outlines the research design, target participants, populations, and sampling types, as well as the methods for data collection, measurement instruments, and techniques for data analysis utilised in this study. The main objective is to create a structured plan that ensures the research is on the right track and the results are reliable.

3.1 Research Design

The concept of research design is central to the integrity of any scholarly investigation, serving as the roadmap for the study. Creswell and Creswell (2017) suggested that research design is a “plan or proposal to conduct research, involves the intersection of philosophy, strategies of inquiry, and specific methods.” It is not just selecting tools; it is an extensive framework of choices, from spanning general assumptions to data collection methods that ensures the research problem is addressed through a structured plan. There are three types of design: quantitative, qualitative and mixed methods.

3.1.1 Quantitative Research

Quantitative research refers to the method of collecting and analysing numerical data to explain the phenomena. It acts to evaluate objective theories by examining the connections between variables. These variables can then be quantified, usually through instruments (like survey), allowing for the analysis of numerical data using statistical methods. The completed written report follows a specific format that includes an introduction, literature and theory, methods, results, and discussion (Creswell, 2008 as cited in Creswell & Creswell, 2017).

3.1.2 Qualitative Research

Qualitative research focuses on understanding experiences, perceptions, and meanings rather than numerical data. It provides a method to investigate and comprehend how people or communities perceive a social or human concern. It involves asking evolving questions and collecting information directly within the participants' real-world settings. The analysis proceeds inductively, transitioning from specific observations to broader themes, as the researcher interprets meaning of the results (Creswell, 2007 as cited in Creswell & Creswell, 2017).

3.1.3 Mixed-Methods Research

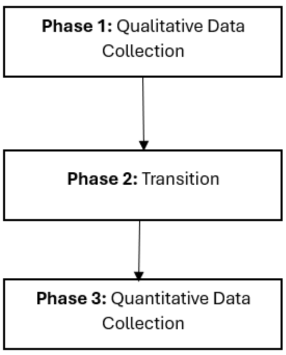
Mixed methods research is an approach combines quantitative and qualitative elements. It is based on particular philosophical beliefs and involves using and blending both types of methods within a single study. Instead of simply collecting and investigating qualitative and quantitative data, this method intentionally integrates them to improve the overall robustness of the research, leading to a more powerful study than employing either technique independently (Creswell & Plano Clerk, 2007 as cited in Creswell & Creswell, 2017).

This study was conducted using mixed-methods design which applying both quantitative and qualitative approaches to explore students' motivation in engaging with AI tools. There are some restrictions if this study solely applies quantitative or qualitative methods. Morgan (2007) critiques the dependence on "mono-methods" by emphasising the artificial division between theory and data. He claims that strictly following a deductive (quantitative) or inductive (qualitative) approaches results in a "fatally limited approach" to research. When researchers only use quantitative approach, they may confine themselves within set boundaries that hinder their ability to "converting observations into theories" and this leads to a decontextualization of the information.

Furthermore, Faizin et al. (2025) also suggest that future studies can enhance quantitative findings with qualitative research in which information is gathered via detailed interviews or focus group conversations to further comprehend students' perspectives on AI tools. Therefore, this study applied mixed method to capture a comprehensive behaviour of individuals towards AI tools and to analysed structured data.

3.2 Data Collection Procedure

Figure 3.1: Data Collection Procedure



Source: Author's Own Elaboration

This study follows an exploratory sequential mixed-methods design, which first collecting qualitative data and then collecting quantitative data. In this study, there are three different phrases: qualitative exploration, transition, quantitative generalisation.

In ***phase 1***, semi-structured interviews were held with 5 students who had experience with AI tools. The interview is conducted using Microsoft Teams or in physical mode, with each interview session lasting around 25-30 minutes, and 5 students participate the interview. To ensure data accuracy, every session was audio-recorded with the participants' consent and later transcribed into text for analysis.

The interview questions were created following a thorough review of existing literature, particularly focusing on SDT and TAM. These questions aimed to investigate students' motivations to use AI and their perceived effects on academic performance. A summary of this theoretical mapping is presented in **Table 3.1**, showing the relationship between each interview questions and research variables. The full list of interview questions is presented in **Table 3.2**.

Table 3.1: Mapping of Interview Questions

Research Variable	Theoretical Framework	Question No.
Background & Usage	-	1,2,3
Autonomy	SDT	4,5
Competence	SDT	6,7
Perceived Usefulness	TAM	8
Perceived Ease of Use	TAM	9
Perceived Academic Performance	-	10
Barriers & Awareness	-	11,12,13

Source: Author's Own Elaboration

In ***phase 2***, after the interviews, we examined the qualitative data to find common themes. These emerging themes provide the contextual "link" needed to enhance the variables for the second phase. Through the combination of qualitative results with the theoretical models of SDT and TAM, questionnaire has successfully created based on the real experiences of the students.

In ***phase 3***, the questionnaire is distributed via Google Forms. This phase intended to evaluate the qualitative findings across a larger student population, enabling the statistical analysis of students' motivation to use AI. The full list of questionnaire questions is presented in **Table 3.3**. The measurement scales were adapted and modified from previous studies. Particularly, elements for the SDT were taken from Hew and Kadir (2016) and Furrer & Skinner (2003). To assess perceived usefulness and perceived ease of use grounded in TAM, measures were modified from the seminal work of Davis (1989). Furthermore, the items measuring behavioural intention to use AI were adjusted from Venkatesh et al. (2003, 2012) and Bhattacherjee (2001). Finally, the scales of AI usage and perceived academic performance were adapted from recent studies by Segbenya et al. (2023), Jaboob et al. (2024), respectively.

3.3 Sampling Design

3.3.1 Target Population

The population targeted for this study includes all undergraduate UTAR students who are presently enrolled in the programmes under Faculty of Accountancy and Management (FAM) in UTAR Sungai Long Campus. These respondents are selected because there is lack of studies focused on this faculty, exploring the deep factors that motivate them to use AI tools.

3.3.2 Sampling Technique

A sample is characterised as a representative portion or segment of a population that is explicitly examined and assessed in a research study. These sampling techniques fall into two main branches: probability sampling (cluster sampling, stratified sampling, systematic sampling, etc), in which each member of the population has a known, non-zero probability of being chosen, and non-probability (convenience sampling, purposive sampling, snowball sampling, etc), where selection relies on convenience or judgement instead of randomness (Pace, 2021).

The research used convenience and purposive sampling to choose the participants. To gather quantitative data, this study utilised convenience sampling, a non-probability technique involving the selection of participants from the target population based mainly on their ease of access and closeness. This approach was selected due to its cost effectiveness and time efficiency (Golzar et al., 2022).

To gather qualitative data, purposive sampling was utilised to ensure the choice of "information-rich cases". This technique was used to pinpoint and interview students with AI experience, as purposive sampling includes the "intentional selection of specific units" according to their specific traits and significance to the research requirements. By focusing on individuals with expertise in AI, the research gained context-relevant insights that a convenient sample could easily miss (Tajik et al., 2024).

3.3.3 Sampling Size

The sample size refers to the total number of participants or other study units needed to address the research questions (Gupta et al., 2016). Specifically, an excessively large sample is only a wastage of resources, expenses, and time, while a sample that is too small does not yield definitive and trustworthy results (Gowda et al., 2019 as cited in Adhikari, 2021). Thus, it is important for researcher to figure out an appropriate sample size to generate reliable results. Considering the target group of 1500 students from the FAM, a recommended sample size of 306 is proposed to meet the standards for quantitative research, as indicated in Krejcie and Morgan (1970) sample size table. In this study, 202 of respondents have been collected.

For qualitative data, the sample size was established according to the principle of information power, indicating that a more information-dense sample necessitates fewer participants (Malterud et al., 2015). In this study, 10 participants were considered adequate due to its narrow aim and high sample specificity, as the interview specifically required students with direct AI experience. Since these participants have specialised knowledge relevant to the questions, the quality of the discussion is assumed to be high, thus providing enough information power to meet the research's objectives without needing a large sample.

In this study, the qualitative sample size was determined by the principle of data saturation, defined as the point at which no additional new issues or insights are identified and data begins to repeat, indicating that further data collection is redundant. According to Hennink and Kaiser (2021), qualitative studies with relatively homogenous study populations and narrowly defined objectives typically reach saturation within narrow range of 9 to 17 interviews.

At this point, core themes regarding students' intention and AI usage became repetitive across participants. To ensure a deeper understanding of the dimensions of these themes, data collection continued until 10th participant.

3.4 Data Collection Method

The quantitative data will be collected via online platforms like WhatsApp, Instagram and XiaoHongShu, alongside on-site distribution at the FAM student lounge and KA Block to gather varied array of respondents from the university. Concurrently, the qualitative data will be collected via Microsoft Teams or Zoom.

3.4.1 Primary Data

For this study, all information gathered is primary data. According to Ajayi (2023), primary data refers to original and distinctive information gathered firsthand by the researcher from a particular source to fulfil their own requirements. In contrast to secondary data, which pertains to historical information, primary data is viewed as current data that is authentic and original. It is collected with the explicit goal of finding a solution to the current research issue, making certain that the data is tailored to the researcher's requirements.

The collection of primary data is characterised as "highly engaging", often demanding considerable time, effort, and financial resources. To address these challenges and ensure effective data collection phase, this study will initiate the collection process few months early. Furthermore, online platforms will be mainly employed for the questionnaires to enhance cost efficiency.

3.5 Research Measurements and Instruments

3.5.1 Measurement Scale

According to Stevens (1946), measurement of scale is described as the allocation of numerals to objects or events based on specific rules. The kind of scale obtained is dictated by the empirical operations conducted, and these scales are divided into four unique categories: nominal, ordinal, interval, and ratio. Understanding these classifications is important as the mathematical group framework of a scale determines which statistical operations can be appropriately performed on the gathered data.

In this study, nominal scale is applied for categorisation and identification, mainly in Section A: Demographic part of the survey. As the most basic level of measurement, it uses numbers as simple labels or type identifiers to classify data, like gender, year of study, programme, etc. The basic principle of this scale is that the same number cannot be allocated to separate categories, and its main aim is to categorise and organise participants into different groups.

Other than that, this study also relies on the ordinal scale, particularly by utilising a 5-point Likert Scale in Sections C to F. This scale enables the arrangement of items according to particular characteristics such as AUT, REL, etc. Although it accurately identifies "greater or less" relationships in students' responses, it does not suggest that the intervals between the ranks. For example, the distance between "Agree" and "Strongly Agree" are mathematically equal.

Additionally, the interval scale and ratio scale denote more complicated quantitative assessments. An interval scale enables the identification of equal differences between values but does not have a true zero point, as illustrated in temperature scales. Conversely, a ratio scale represents the most advanced type of measurement, incorporating all the characteristics of the earlier scales combined with a true zero point. This absolute zero allows for the assessment of ratio equality, which is common in physical measurements such as weight, age, etc.

3.5.2 Interview Design

This study utilises the semi-structured interview, characterised as an exploratory research technique that relies on an interview guide centred on a main theme to provide a general pattern. In contrast to strict questionnaire, this approach is seen as an "inter-view", which is a dialogue between individuals discussing a topic of shared interest. By using this approach, the researcher able to gather detailed information and insights from participants while rigorously keeping the study's focus. Moreover, the approach provides substantial flexibility, allowing the researcher to ask follow-up questions in order to have deeper understanding on participants' personal experiences (Mashuri et al., 2022). In this interview, participants will share their distinct experiences with AI tools to explore their motivations and challenges to use AI.

3.5.3 Questionnaire Design

The questionnaire of this study consists of following sections:

In Section A, an acknowledgement of notice will be presented to participants to ensure they are fully aware that their information will be applied exclusively for this study. This section is implemented to protect participant privacy and maintain strict data confidentially.

In Section B, participants are initially requested to state if they have previously engaged with AI tools and to specify the frequency of usage. This session is served as the preliminary screening phase. Moreover, participants will need to choose which AI tools that have been used. To ensure the data's validity and relevance, an eligibility requirement is implemented: participants who choose "No" on using AI tools in their studies are automatically excluded from this study.

In Section C, assessments about motivation to use AI will be asked to evaluate the underlying reasons and motivations that prompt individuals to engage with AI and in which aspects of study that they are using AI tools.

In Section D, students' behavioural intention to use AI will be assessed: "Will they continued using AI in the future?".

In Section E, it focuses on the actual frequency and nature of AI usage to investigate the relationship between behavioural intention to use AI and their actual AI usage.

In Section F, students will be examined the perceived impact of AI tools on their perceived academic performance.

3.6 Constructs Measurement

3.6.1 Origin of Constructs

Table 3.2: Full List of Interview Questions

No.	Interview Question
1	What kind of AI tools do you commonly use?
2	What are your purposes to use AI tools?
3	What are your motivation factors to use AI tools in your studies?
4	Do AI tools allow you to approach your learning in your own way? How?
5	Can you use AI tools freely in your studies?
6	How confident are you in using AI tools to complete your academic tasks?
7	Do you think you become more competent in your studies after using AI tools?
8	In your opinion, how useful are AI tools for your learning or coursework?
9	Do you think it is easy to use AI tools?
10	From your experience, how has using AI tools influenced your academic performance?
11	What are the main challenges or difficulties you face when using AI tools for your studies?
12	Have you ever received unclear or incorrect answers from AI tools? How did you handle that?
13	How aware are you of the capabilities of generative AI tools, such as ChatGPT, in supporting your academic tasks?

Source: Author's Own Elaboration

Table 3.3: Full List of Questionnaire Items

Variable	Item No.	Original Item	Adapted Item	Author(s)
Autonomy	AUT 1	I feel like I can make a lot of inputs in deciding how I use VLE in my teaching profession.	I decide how I use AI tools in my studies.	(Hew & Kadir, 2016)
	AUT 2	I feel pressured at using VLE in my teaching profession.	I feel pressured when I use AI tools in my studies.	
	AUT 3	I am free to express my ideas and opinions on using VLE in my teaching profession.	I am free to express my ideas on how I use AI tools.	
	AUT 4	When I am using VLE, I have to do what I am told.	I follow my lecturer's guidance on how to use AI tools.	
	AUT 5	My feelings toward VLE are taken into consideration at work.	I care my feelings when I use AI tools in my studies.	
	AUT 6	I feel like I can pretty much use VLE as I want to at work.	I can use AI tools in ways that suit my learning style.	
	AUT 7	There is not much opportunity for me to decide for myself how to use VLE in my teaching profession.	I have opportunities to decide how I want to use AI tools.	
Competence	COM 1	I do not feel very competent when I use VLE in my teaching profession.	I feel very competent when using AI tools in my studies.	(Hew & Kadir, 2016)
	COM 2	The other colleagues tell me I am good at	My peers tell me I am good in	

		using VLE in my teaching profession.	using AI tools for my studies.	
	COM 3	I have been able to learn interesting new skills in VLE through my profession.	I have learned new skills by using AI tools.	
	COM 4	Most days I feel a sense of accomplishment from working with VLE.	I feel a sense of accomplishment when I use AI tools in my studies.	
	COM 5	As a teacher I do not get much of a chance to show how capable I am in VLE.	I have many chances to show my capability in using AI tools.	
	COM 6	When I am using VLE I often do not feel very capable.	I feel capable when I use AI tools for learning tasks.	
Relatedness	REL 1	I feel accepted.	I feel accepted by my peers when I use AI tools in my studies.	(Furrer & Skinner, 2003)
	REL 2	I feel like someone special.	I feel valued when participating on using AI tools.	
	REL 3	I feel ignored.	I do not feel ignored when I use AI tools.	
	REL 4	I feel unimportant.	I feel it is important to use AI tools in my studies.	
Perceived Usefulness	PU 1	Using the system would enable me to accomplish tasks more quickly.	Using AI tools helps me complete my assignments more quickly.	(Davis, 1989)
	PU 2	Using the system would improve my job performance.	Using AI tools helps improve my academic performance.	

	PU 3	Using the system would increase my productivity.	AI tools make me a more productive student.	
	PU 4	Using the system would make it easier to do my job.	AI tools make me easier to manage my studies.	
	PU 5	I would find the system useful in my job.	I find AI tools useful for my studies.	
	PU 6	Using the system would enhance my effectiveness on the job.	AI tools increase my effectiveness as a student.	
Perceived Ease of Use	PEOU 1	Learning to operate the system would be easy for me.	Learning how to use AI tools is easy for me.	(Davis, 1989)
	PEOU 2	I would find it easy to get generative AI to do what I want it to do.	I find it easy to get AI tools to do what I need for my studies.	
	PEOU 3	My interaction with generative AI would be clear and understandable.	I can interact with AI tools easily.	
	PEOU 4	I would find generative AI flexible to interact with.	I find AI tools flexible enough for my studies.	
	PEOU 5	It would be easy for me to become skillful at using the system.	It is easy for me to become skilful at using AI tools.	
	PEOU 6	I would find the system easy to use.	AI tools are easy for me to use.	
Behavioural Intention to Use	BIU 1	I intend to use the system in the future.	I intend to use AI tools for my learning in future courses.	(Bhattacherjee, 2001)
	BIU 2	I predict I will use the system in the future.	I expect myself to continue to use AI tools in my studies.	

	BIU 3	I plan to use the system in the future.	I plan to use AI tools whenever it is available for my studies.	
	BIU 4	I intend to continue using OBD rather than discontinue its use.	I intend to keep using AI tools rather than stop using them.	
	BIU 5	My intentions are to continue using OBD rather than use any alternative means.	I prefer to use AI tools instead of other methods.	
	BIU 6	If I could, I would like to discontinue my use of OBD.	I intend to use AI tools for my studies instead of stop using it.	
AI Usage	AIU 1	Just used for learning in general	I use AI tools for general learning purposes	(Segbenya et al., 2023)
	AIU 2	Searching for literature	I use AI tools for searching for academic literature	
	AIU 3	Writing an assignment	I use AI tools for writing assignments	
	AIU 4	Writing a postgraduate dissertation, thesis, or long essay	I use AI tools for working on long essays, theses, or major projects	
	AIU 5	Writing term papers	I use AI tools for writing term papers	
	AIU 6	Writing an undergraduate project work	I use AI tools for doing undergraduate project work	
	AIU 7	Writing commands for software	I use AI tools for coding or generating commands	
	AIU 8	Preparing power points	I use AI tools for preparing PowerPoint slides	

	AIU 9	Writing an article for publication	I use AI tools for writing or drafting academic articles	
Perceived Academic Performance	AP 1	I believe that Generative AI Techniques and Applications have positively influenced my cognitive abilities and academic performance.	AI tools have improved my academic performance.	(Jaboob et al., 2024)
	AP 2	The integration of Generative AI has enhanced my problem-solving skills and critical thinking.	AI tools have helped me improve my problem-solving and critical thinking skills.	
	AP 3	Generative AI Techniques and Applications have contributed to higher cognitive achievement in education.	AI tools help me to achieve higher academic performance.	
	AP 4	I have noticed improvements in my academic performance due to the use of Generative AI	I see improvement in my academic performance because I use AI tools	
	AP 5	Generative AI Techniques and Applications have positively influenced my cognitive abilities and academic success.	AI tools have helped me be more successful in my studies.	
	AP 6	The integration of Generative AI has positively impacted my academic	Overall, AI tools have positive influences on	

		performance and cognitive abilities.	my academic performance.	

Source: Author's Own Elaboration

3.7 Data Processing

3.7.1 Qualitative Data Processing

Step 1: Data Preparation

The first stage of qualitative processing includes preparing data, mainly by transcribing interviews and field notes to transform them into an accessible format. As stated by Ruona (2005), this stage is not just mechanical; it involves "cleaning" the data by making minor edits and adjustments to ensure it is prepared for thorough research.

Step 2: Anonymisation

In this stage, steps are taken to safeguard the identity of the participants as guaranteed in the ethical approval. The researcher will need to assign pseudonyms or code numbers to interviewees (e.g., *Respondent 1, 2, 3…*). A secure and private master file is kept associating these codes with the original informants, while all names and identifiable information are consistently eliminated from the transcripts to protect participants confidentially (Ruona, 2005).

Step 3: Familiarisation

In this stage, the researcher will need to engage much more deeply into the gathered data. Usually, this involves hearing the audio recordings and repeatedly reading transcripts while taking notes and memos at the same time about the insights and analysis of the data's dynamics. The researcher needs to actively interact with the material, essentially having a "conversation" with the data by questioning it and providing comments (Merriam, 1988 as cited in Ruona, 2005). It allows the researcher to tune into the messages from the participants and recognise remarkable data points that will be crucial for the following phases of the analysis.

Step 4: Coding

The last stage in the data processing involves using coding to arrange information into significant categories. Ruona (2005), referencing Miles and Huberman (1994), characterises this as the essence of analysis. This procedure includes dividing sentences or paragraphs into groups and tagging them with particular terms (Creswell, 2003). Coding fulfils two roles: it functions as data simplification by reducing complex data into general categories, and as data complication, wherein the researcher examines the data to uncover new dimensions of interpretation (Coffey & Atkinson, 1996 as cited in Ruona, 2005).

3.7.2 Quantitative Data Processing

Step 1: Data Cleaning

This phase focuses on identifying and eliminating errors and inconsistencies to enhance data quality. It includes filling in missing values caused by input mistakes, refining "noisy" data through binning or regression, and detecting outliers that may result in incorrect results (Calabrese, 2018; Sharifnia et al., 2025).

Step 2: Data Coding

This phase includes giving numerical values to categorical data to make it "machine-readable" for later analysis. For example, Male is coded as 1 and Female is coded as 2, as shown in **Table 3.4.**

Step 3: Reverse Coding

In this phase, scores for questions phrased negatively will be flipped to align them with the positively stated ones. For instance, "I feel pressured when I use AI tools in my studies" indicates a negative emotion. To align these positive inquiries, a "Strongly Agree" answer (initially a 5) was recoded to a 1, while a "Strongly Disagree" response (initially a 1) was recoded to a 5.

According to Zhang et al. (2016), applying these backwards questions is a typical method t6o ensure participant engagement, yet they may lead to a "method effect" that distorts the outcomes due to the phrasing. Through reverse coding of these items, the researcher ensured that all high numerical scores throughout questionnaire consistently represent the same thing. This alignment is essential to avoid inaccuracies in the final statistical model and to guarantee the data genuinely represents the students' real opinions.

Step 4: Data Entry

The last phase involved the systematic transfer of the cleaned and coded Excel spreadsheet from Google Forms into SPSS. This completed the dataset, preparing it for the application of descriptive and inferential analysis.

Table 3.4: Questionnaire Data Coding

Section A		
Constructs	**Measurement**	**Coding**
Acknowledgement of Notice	Nominal	1 = Agree 2 = Disagree
Gender	Nominal	1 = Female 2 = Male
Programme of Study	Nominal	1 = Bachelor of Accounting 2 = Bachelor of Economics (Honours) Global Economics 3 = Bachelor of Building and Property Management (Honours) 4 = Bachelor of Finance (Financial Technology) with Honours 5 = Bachelor of International Business (Honours)
Year of Study	Nominal	1 = Year 1 2 = Year 2 3 = Year 3 4 = Year 4
Have you ever used AI tools in your studies?	Nominal	1 = Yes 2 = No
What types of AI tools have you used for your academic work?	Nominal	1 = One tool used 2 = Two tools used 3 = Three tools used 4 = Four tools used 5 = Five tools used
How frequently do you use AI tools for your academic tasks?	Ordinal	1 = Daily 2 = Weekly 3 = Monthly 4 = Rarely 5 = Never

Section B, C, D, E

Constructs	Measurement	Coding
Autonomy Relatedness Competence Perceived Usefulness Perceived Ease of Use Behavioural Intention to Use AI AI Usage Perceived Academic Performance	Ordinal (Likert Scales)	1 = "Strongly Disagree" 2 = "Disagree" 3 = "Neutral" 4 = "Agree" 5 = "Strongly Agree"

Source: Author's Own Elaboration

3.8 Proposed Data Analysis Tool

3.8.1 Qualitative Analysis

In this study, the data obtained from interviews will be analysed using thematic analysis. According to Lochmiller (2021), thematic analysis will be applied to recognise repeated patterns and transform them into significant themes. The procedure consists of three stages: initially, the researcher arranges the data; next, the researcher performs "coding" to identify important concepts and groups these into wider categories; and finally, the researcher links these categories to create themes. This organised "build up" from minor details to major themes ensure that the outcomes are precisely grounded in the participants' actual words. The example is presented in **Table 3.5**.

Table 3.5: Thematic Analysis Process

Step	Definition	Example
1. Codes	Labels for specific phrases	"Save time", "Better Grades"

2. Categories	Grouping similar codes together	Category A: Motivation Category B: Academic Results
3. Themes	Big picture	AI as an Efficient Tool for Academic Success

Source: Author's Own Elaboration

3.8.2 Quantitative Analysis

The quantitative data will be analysed with IBM SPSS. This software enables the study to refine and organise the dataset. By examining the relationships among variables via SPSS allows the study to make informed decisions and apply effective strategies grounded in the results.

3.8.2.1 Descriptive Analysis

Descriptive statistics summarise data systematically by illustrating the connections between variables within a sample or population. This study examines nominal variables through frequencies and percentages to illustrate how often specific values occur. Absolute frequency indicates the total count of occurrences, whereas percentages present these figures as a portion of the overall sample for better understanding. These frequency measures are commonly represented with bar graphs to make the information more accessible. For data measured on ordinal scales, the mean, mode, and standard deviation are used to represent the central tendency and variability of the dataset (Kaur et al., 2018).

3.8.2.2 Reliability Test

Cronbach's alpha is a method for assessing reliability that provides a unique estimate of internal consistency for a multi-item scale. It shows the mean value of reliability coefficients expected for every potential combination of items. Cronbach's alpha is designed for scales or subscales that consist of several items and is not able to offer reliability estimates for questions with a single item.

The resulting coefficient typically falls between 0 and 1, with a value nearer to 1.0, indicating higher internal consistency among the items in that scale. The overall size of the alpha coefficient is mainly influenced by two elements: the total count of items in the scale and the average of the inter-item correlations. Generally, researchers target an alpha of .8 as a practical objective for confirming the scale's reliability (Gliem & Gliem, 2003). The interpretation of Cronbach's alpha is presented in **Table 3.6**.

Table 3.6: Range of Reliability

No	Coefficient of Cronbach's Alpha	Reliability Level
1	$\alpha \geq 0.9$	Excellent
2	$0.9 > \alpha \geq 0.8$	Good
3	$0.8 > \alpha \geq 0.7$	Acceptable
4	$0.7 > \alpha \geq 0.6$	Questionable
5	$0.6 > \alpha \geq 0.5$	Poor
6	$0.5 > \alpha$	Unacceptable

Source: Adopted from George and Mallery (2019)

3.8.2.3 Inferential Analysis

Inferential statistics are computed to extend results from a particular sample to a whole population of interest. While descriptive statistics only provide an overview of what happened in the sample, whereas inferential statistics enable researchers to assess whether differences seen between groups (Allua & Thompson, 2009).

3.8.2.3.1 Pearson's Correlation Analysis

This study will apply the Pearson correlation coefficient (*r*) to explore the relationships between student motivation, behavioural intention to use AI, AI usage, and perceived academic performance. The Pearson correlation coefficient (*r*) is a statistical method used to assess the strength and direction of a linear relationship between two continuously measured variables. According to Plonsky (2015), Pearson's *r* is a common statistic in second language studies for determining the relationship between changes in one continuous variable and changes in another. The interpretation results range are as shown in **Table 3.7**.

Table 3.7: Interpretation of *r*

Correlation Coefficient	Strength
0 - 0.19	Very weak
0.20 - 0.39	Weak
0.40 - 0.59	Moderate
0.60 - 0.79	Strong
0.80 - 1.0	Very strong

Source: Adopted from Evans (1996)

3.8.2.3.2 Multiple Linear Regression Analysis

Multiple linear regression is used to model the relationship between one dependent variable and two or more independent variables. It expands on basic linear regression by enabling researchers to explore how multiple factors interact to predict the specific outcome. This approach is especially effective in pinpointing which particular independent variables are the most significant predictors of the outcome under investigation.

The main objective of multiple regression is to determine how much of the total variance in the dependent variable can be accounted for by the combined group of independent variables. This is measured by the coefficient of multiple determination, known as R^2. A greater R^2 suggests that the model's predictors are more effective at clarifying the variations in the dependent variable.

The study will need to analyse the results via evaluating the F-test and its corresponding p-value. When the p-value is below the selected α level, it suggests that the independent variables significantly forecast the dependent variable. This verifies that the relationship observed is not based on random chance.

Finally, this study will also analyse the regression coefficients (β) for every single independent variable. These coefficients reflect the direction (positive or negative) and the strength of each individual predictor's distinct impact on the outcome while keeping all other variables unchanged (Jeon, 2015).

3.8.2.3.3 Multicollinearity

Multicollinearity occurs when a multiple linear regression analysis incorporates various variables that are strongly correlated, not just with the dependent variable, but also with one another. Multicollinearity causes certain significant variables being analysed to appear statistically insignificant. A VIF value of 1 indicates that the independent variables have no correlation with one another. When the VIF value falls between 1 and 5, it shows a moderate correlation among the variables. The critical VIF range is between 5 and 10 as it indicates the presence of highly correlated variables (Shrestha, 2020).

3.8.3 Model Specification

Model 1:

$$BIU_t = \beta_0 + \beta_1 AUT_t + \beta_2 COM_t + \beta_3 REL_t + \beta_4 PU_t + \beta_5 PEOU_t + \varepsilon_t$$

Model 2:

$$AIU_t = \beta_0 + \beta_1 BIU_t + \varepsilon_t$$

Model 3:

$$AP_t = \beta_0 + \beta_1 AIU_t + \varepsilon_t$$

3.9 Pre Test

Pre-test is an important stage in the creation, modification or translation of any questionnaire or psychometric tool. The primary aim of the pre-test is to ensure that the participant comprehends the questions and suggested response choices as the researcher intends and is truly capable of responding in a meaningful way (Perneger et al., 2014). It functions as an initial test to identify "problem", such as vague questions, unknown phrases, unclear sentence structures, absent time frames, or insufficient suitable response choices.

In this study, the pre-test was conducted by giving the instruments to a limited number of participants. To assess the clarity of the research instruments, two self-report questions were included at the end of both the questionnaire and the interview: (1) *"Were any of the questions difficult to understand?"* and (2) *"If Yes: Please specify which question number(s) and why"*. Every participant stated that the questions were understandable, and no amendment needed were mentioned.

3.10 Conclusion

This chapter explains the methodology implemented in this study, outlining the research design, target population, sampling size, sampling technique, data collection procedures, data processing, measurement of scales, and proposed analytical tools.

CHAPTER 4: DATA ANALYSIS

4.0 Introduction

The analysis and discussion of collected quantitative and qualitative data will be involved in this chapter. The qualitative data will be categorised into six (6) themes and quantitative data will be analysed by IBM SPSS.

4.1 Thematic Analysis

This section presents the main findings from interviews with 10 UTAR students, focusing on their experiences in using AI and the challenges they faced while using it. Thematic analysis revealed six key themes: (1) Functional Value and Efficiency, (2) System Accessibility and User Interaction, (3) Student Agency and Personalisation, (4) Skill Mastery and Confidence, (5) Impact on Perceived Academic Performance and (6) Navigational Challenge and Ethical Barriers.

4.1.1 Functional Value and Efficiency

This theme suggest that AI's function and efficiency are the primary drivers that motivate students to engage with AI tools, which directly corresponds with perceived usefulness (PU) construct within TAM framework. Most interviewers think that AI tools act as a time-saving mechanism. Students like *Respondent 2, Respondent 3, Respondent 5* and *Respondent 6* explicitly mentioned that AI tools like Gemini, ChatGPT, Perplexity, etc, serve as a convenient space for gathering and summarising information. This saves them from the tedious work of sifting through multiple search engine results. For instance, *Respondent 3* highlighted the aspect of "automation", explaining that AI can organise and process information far faster than human. *Respondent 6* further support this point, saying that she often relies on AI because it saves her hours of manual study time. Together, their experiences indicate that students adopt AI primarily for practical reasons: they treat it as a direct boost to their productivity and academic efficiency.

Beyond mere speed, the functional value of AI is also deeply rooted in its role as a cognitive support tool that enhances comprehension. Several respondents, including *Respondent 1, Respondent 7, Respondent 8, Respondent 9 and Respondent 10*, reported using AI to clarify complex academic concepts and lecture materials. *Respondent 8* noted that she uses AI to "shorten" dense lecture slides into digestible notes, while *Respondent 7* valued the tool's ability to illustrate "extra examples" that provide a broader perspective that the textbook alone. This indicates that the "usefulness" of AI extends beyond finishing assignments quickly and shorten study time; it serves as a bridge to understanding difficult content. When students like *Respondent 9* and *Respondent 4* observe that AI provides different viewpoints and clear explanations, their perceived usefulness of the technology increases, thereby strengthening their motivation to integrate AI tools into their daily academic routines.

"It can illustrate extra examples that I do not think of." (Respondent 7)

"Some of the lecture slide will be provided much information then I will ask the AI to make it shorter and easy to understand in order to let me easily to prepare my final." (Respondent 8)

These findings highly align with the concept of Perceived Usefulness (PU), when a person feel that AI can increase their productivity and efficiency, they are more willing to use AI.

4.1.2 System Accessibility and User Interaction

The second theme identifies the seamless nature of user interaction and the low technical barriers to entry, aligning with the Perceived Ease of Use (PEOU) construct of the TAM. Among these 10 interviews, every respondent mentioned that AI tools have "near-zero learning curve", describing that it is intuitive and user-friendly that users can master them immediately without any lessons. Students such as *Respondent 3, Respondent 4* and *Respondent 5* specifically highlighted that the "simple design" and "user-friendly interfaces" as main reasons for their quick adoption.

"I feel like it is very easy to use AI because the way that they design it is very simple." (*Respondent 3)*

"It is quite easy because most AI tools have simple interfaces and are user-friendly." (Respondent 5)

Respondent 4 noted that the interaction is as simple as typing a question and receiving immediate response "within seconds". This is further supported by *Respondent 9* and *Respondent 10*, who both categorise the tool as "Easy". This reinforces the idea that accessibility is a common experience among undergraduate students regardless of their academic background.

"AI has simple interfaces, and I usually just type my question and it will provide a response within seconds." (Respondent 4)

Moreover, respondents emphasised its characteristics of "anytime, anywhere" accessibility and the convenience of multi-modal inputs. *Respondent 6* highlighted that the ability to use AI at any moment and from any location makes it a more attractive option than seeking help from lecturers or peers who may not be immediately available. Furthermore, *Respondent 7* provided example of how "Ease of Use" can be maximised through specific features, noting that he finds the tool easiest to use when he can simply "screenshot" a difficult question instead of typing it out. Similarly, *Respondent 8* described it as a "one-click" process. This high level of Perceived Ease of Use (PEOU) is a significant driver to use AI. As what mentioned by *Respondent 1* and *Respondent 2*, when the effort required to use the tool is perceived as minimal, students are more willing to engage with AI for a wider range of academic purposes.

"I can use anytime and anywhere." (Respondent 6)

"It is easy to use when I can screenshot the question instead of typing the full question out." (Respondent 7)

"AI is easy to use, as I just need to search and one click then the AI will reply to me." (Respondent 8)

4.1.3 Student Agency and Personalisation

This theme emphasises that how AI tools allow students to tailor their learning styles to strengthen their autonomy. This directly reflects the Autonomy component of SDT, which stresses the value of self-directed behaviour. All 10 respondents shared that AI provides a level of customisation they rarely experience in traditional classroom settings. For example, *Respondent 1* and *Respondent 2* mentioned that they are able to ask for explanations in "simple English", helping them overcome language barriers and control how complex the information should be, which is something textbooks rarely allow. Likewise, *Respondent 3* and *Respondent 4* described using AI to summarise content according to their personal revision preferences, placing themselves in charge of their own learning process.

"I can ask AI to explain an information to me in simpler term. Make me much easier to understand." (Respondent 3)

"I can ask AI to explain concepts in simpler terms and summarize materials based on my learning preferences." (Respondent 4)

This sense of control is also seen in how students manage their learning pace. *Respondent 5* and *Respondent 8* highlighted the "patience" of AI tools, with *Respondent 8* noting that AI tool will continue to explain the concept until she understand. This helps her learn independently without the discomfort of asking a lecturer for repeated clarification. *Respondent 7* also used AI to "cross-check" his own logic—not treating it as an absolute authority, but as a sounding board to refine his thinking. *Respondent 9* and *Respondent 10* gave a similar opinion, explaining that AI tools enable them to "tailor their learning style" to fit their own study context. AI gives students a stronger sense of control over their learning, which plays a crucial role in keeping them motivated and engaged in the long run.

"It will continue explain until me understand and provide more example for me. I also appreciate to its patience as I can repeatedly ask the same question without feeling any uncomfortable." (Respondent 8)

"AI allows me to cross-check my logic." (Respondent 7)

4.1.4 Skill Mastery and Confidence

This theme focuses on the enhancement of academic competence and the development of student confidence through AI integration. Regarding to SDT framework, the feeling of being "competent" is an important intrinsic motivator. Respondents reported that AI tools make them feel more capable of handling complex tasks. *Respondent 1* and *Respondent 2* both noted that AI helps them to connect their scattered ideas into a "natural flow" for presentation. Other than that, they also mentioned that it enhances their "writing" and "thinking" skills. Similarly, *Respondent 3* observed that AI makes his writing "more clever" and professional, which leads to a greater sense of efficacy when submitting work to lecturers. Additionally, *Respondent 9* and *Respondent 10* both highlighted that AI fosters "independent thinking" as it provides different viewpoints that they might not have considered.

"AI helps link scattered ideas together into a natural flow and assists in preparing presentations by simplifying complex terms." (Respondent 2)

"AI tries to improve your ideas and try to make your writing cleverer and in more professional way." (Respondent 3)

"AI gives us the viewpoint that we didn't think of which is very new and assists us to think in different way." (Respondent 9 and 10)

However, even the AI tools enhanced their skills. Some respondents such as *Respondent 1, Respondent 2, Respondent 3* and *Respondent 7,* remain more cautious with a 50% confidence level due to potential AI errors like wrong information provided. This might require respondents to critically evaluate and "double check" rather than blindly following the technology.

"Rates confidence at a 5 out of 10. Believes basic knowledge is necessary because AI can be misleading and has admitted to making mistakes when questioned." (Respondent 2)

"I have around 50% of confidence on AI. Because sometimes AI will generate a wrong information to us." (Respondent 3)

"50% confidence on AI. I believe we cannot solely rely on AI." (Respondent 7)

4.1.5 Students' Perceived Academic Performance

The fifth theme illustrates the perceived correlation between AI tool usage and academic performance from students' perspective. Every respondent highlighted that AI has positive influence on their academic results. Students like *Respondent 6* and *Respondent 9* perceived a link between their AI usage and the attainment of "higher coursework marks" and an overall "improvement in GPA." For these students, AI viewed as a great assistant for them to meet their own and university requirement. Simultaneously, *Respondent 10* and *Respondent 3* highlighted that their results improved because the AI helped them to polish their work and present ideas in professional way, which they felt lecturers are more likely to reward them with higher marks.

Beyond self-reported grades, the impact on performance is reflected in the students' perceptions of their own preparation. As what *Respondent 1* and *Respondent 2* mentioned above, students found that AI was able to translate difficult textbook content into simpler terms leads to better retention for exams. *Respondent 8* further supported this by explaining that she uses AI to condense extensive lecture slides into concise notes, which she perceived as facilitating a more efficient and effective final preparation. During peak revision periods, AI facilitates significant time savings in note organisation, allowing students to navigate the demands of multiple subjects more effectively. These AI-generated materials enable students to feel they have developed a clearer understanding of the content, which ultimately leads to a smoother expression of ideas in their final examinations.

4.1.6 Navigational Challenge and Ethical Barriers

The final theme identifies the technical, linguistic, and ethical obstacles that students must navigate when using AI tools. While the previous themes establish a strong motivation for use, all 10 respondents acknowledged that the journey is not without challenges. A primary concern of *Respondent 1* and *Respondent 2* involves the structural limitations of the tools themselves, such as hitting "maximum capacity" on pro versions or encountering unexpected linguistic shifts, like the AI responding in Chinese instead of English, which is totally different with what requires by them. These barriers represent a disruption in the Perceived Ease of Use, as they require student to keep communicating with AI tools in different way and troubleshoot financial constraints. For *Respondent 6*, these challenges are strictly technical, citing "system breakdowns" or maintenance periods as the only significant obstacle to her.

"Sometimes AI will generate the answer in totally different language which I need to repeat and clarify my question again." (Respondent 1)

"Most of the time will hit maximum capacity limits on free versions, requiring a purchase for unlimited use." (Respondent 2)

In addition, another significant barrier is the issue of AI's logical inaccuracies. *Respondent 3, Respondent 4* and *Respondent 8* expressed a refined skepticism toward AI outputs, with *Respondent 3* mentioning that he is only "50% confident" due to the risk of receiving wrong information. *Respondent 1* and *Respondent 2* also supported this point, highlighting that "we must use our common sense and basic understanding to identify the accuracy of information." Similarly, *Respondent 9* pointed to "Math errors" as a specific failure in the AI's logic, while *Respondent 10* and *Respondent 7* noted that the AI occasionally "misunderstands" the intent of their prompts or fails to answer the question asked.

"AI will calculate the math questions incorrectly or apply the wrong formulae." (Respondent 9)

"Sometimes AI will misunderstand the questions and fail to answer it in a right way." (Respondent 10)

Last but not least, the analysis reveals a most concerning challenges by universities which is ethical and institutional boundaries. *Respondent 1* explicitly raised the issue of academic integrity, emphasising that while AI did generate ideas for students, they need to be aware not to "copy the answer directly." This ethical awareness is matched with the institutional constraints mentioned by *Respondent 5*, who found that some universities courses actually prohibit students from using AI. While AI tools can make students' academic journey in more effective way, it is important for them to balance its functional value and ethical responsibility.

4.2 Descriptive Analysis

4.2.1 Demographic Profile

Table 4.1: Summary of Demographic Profile

Demographic	Frequency	Percent (%)
Gender		
Female	122	60.4
Male	80	39.6
Programme of Study		
Bachelor of Accounting (Honours)	71	35.1
Bachelor of Economics (Honours) Global Economics	22	10.9
Bachelor of Building and Property Management (Honours)	13	6.4
Bachelor of Finance (Financial Technology) with Honours	70	34.7
Bachelor of International Business (Honours)	26	12.9
Year of Study		
Year 1	34	16.8
Year 2	83	41.1
Year 3	77	38.1

Year 4	8	4.0
Total	202	100

Source: Author's Own Elaboration

The survey reached a total of 202 respondents. As shown in Table 4.1, 60.4% of the respondents were identified as female, while male respondents comprised the remaining 39.6%. In terms of programme of study, most of the students were from Bachelor of Accounting (Honours), which accounting for 35.1%, followed by Bachelor of Finance (Financial Technology) with Honours, which accounting for 34.7%. Other respondents were from Bachelor of International Business (12.9%), Bachelor of Economics (Honours) Global Economics (10.9%), and Bachelor of Building and Property Management (Honours) (6.4%). Furthermore, the data disclose that Year 2 students formed the largest group at 41.1%, followed closely by Year 3 students at 38.1%. At the same time, Year 1 and Year 4 students represented a smaller portion of the sample, at 16.8% and 4.0% respectively.

4.2.2 General Information

Table 4.2: Summary of General Questions

General Information	Frequency	Percent (%)
Have you ever used AI tools in your studies?		
Yes	202	100
No	0	
What types of AI tools have you used for your academic work?		
One tool used	27	13.4
Two tools used	55	27.2
Three tools used	106	52.5

Four tools used	9	4.5
Five tools used	5	2.5
How frequently do you use AI tools for your academic tasks?		
Daily	134	66.3
Weekly	67	33.2
Monthly	1	0.5
Total	202	100

Source: Author's Own Elaboration

Table 4.2 shows that 100% respondents have used AI tools in their studies before. Moreover, majority of respondents which accounting for 52.5%, has used three different AI tools (e.g., Gemini, ChatGPT, etc), followed by 27.2% who utilised two tools. There are small groups of respondents used either one tool (13.4%), four tools (4.5%) or five tools (2.5%). This survey also includes the frequencies of students using AI. 66.3% of the respondents use AI tools daily, 33.2% of them use it weekly and only a negligible 0.5% use it monthly.

4.2.3 Descriptive Statistics

Table 4.3: Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
AUT	202	1.57	5.00	4.3522	.42276
REL	202	1.50	5.00	4.3874	.47839
COM	202	1.00	5.00	4.0239	.84256
PU	202	1.00	5.00	4.5446	.43218
PEOU	202	1.00	5.00	4.3721	.49375
BIU	202	1.00	5.00	4.4183	.47846
AIU	202	1.00	5.00	4.2778	.57112
AP	202	1.00	5.00	4.3383	.56743
Valid N (listwise)	202				

Source: Author's Own Elaboration

Table 4.3 presents the for the dependent variable (AP), mediating variables (AIU, BIU), and independent variables (REL, COM, PU, PEOU). This table clearly shows the central tendency, variability and distribution of the data collected. Across all constructs, the mean scores range from 4.0239 to 4.5446. According to Moidunny (2009), mean score falls between 3.21-4.20 is considered high, while scores ranging from 4.21-5.00 are considered very high. PU has the highest mean (4.5446), which implies that the students believe AI tools will enhance their efficiency. AUT (4.3522), REL (4.3874), and COM (4.0239) also have high mean scores, indicating that the students have intrinsic motivation for the use of AI, as supported by SDT. Moreover, BIU (4.4183) and AIU (4.2778) suggest that students already engage with AI tools in the practice and intend to use it continuously in future. The AP (4.3383) also suggest that students believe AI tools has positive effect on their perceived academic performance. The standard deviatios of all variables were found to be low, which means that these was consistency in the responses of the participants,

In conclusion, the results show that students hold generally positive perceptions of AI, holding all mean scores above 4,0 on average. This reflects an acceptance of AI is strongly linked to SDT and TAM theory to explain their behaviours.

4.2.4 Normality Test

Table 4.4: Results of Skewness and Kurtosis

Variables	Skewness		Kurtosis	
	Statistic	Std. Error	Statistic	Std. Error
AUT	-1.999	.171	9.185	.341
REL	-1.925	.171	6.943	.341
COM	-1.034	.171	.020	.341
PU	-3.398	.171	23.201	.341
PEOU	-1.721	.171	9.574	.341
BIU	-2.505	.171	14.848	.341
AIU	-1.293	.171	4.261	.341
AP	-1.388	.171	4.625	.341

Source: Author's Own Elaboration

Table 4.4 shows the results of the normality testing through Skewness and Kurtosis for the variables. According to Hair et al. (2010), data should follow a normal distribution if Skewness values fall between -2 to +2 and Kurtosis values fall between -7 to 7. The results indicate that variables such as COM, AIU, and AP fall within the ideal range, others like PU and BIU present higher Skewness (-3.398 and -2.505) and Kurtosis (23.201and 14.848) which exceed the typical range. This can be attributed to the consistency of positive responses from the 202 respondents, which represents a consensus among them about the usefulness of AI tools. Moreover, as Tabachnick and Fidell (2013) state, the effect of non-normality is reduced with large sample sizes (>N=200). As this study consists of 202 respondents, the underestimated variance due to the high Kurtosis is statistically neutralised. The data is still valid for parametric testing.

4.2.5 Reliability Test

Table 4.5: Cronbach's Alpha

Variables	No. of Items	Cronbach's Alpha	Reliability Level
AUT	7	0.555	Poor
REL	4	0.682	Questionable
COM	6	0.928	Excellent
PU	6	0.826	Good
PEOU	6	0.782	Acceptable
BIU	6	0.783	Acceptable
AIU	9	0.892	Good
AP	6	0.823	Good

Source: Author's Own Elaboration

From Table 4.5, COM has the highest Cronbach's alpha value of 0.928, which achieving an excellent reliability. Moreover, PU, AIU and AP also show a good reliability with the value of 0.826, 0.892 and 0.823. While PEOU and BIU exhibit an acceptable reliability with the value of 0.782 and 0.783. However, REL has a questionable Cronbach's alpha value of 0.682. According to Daud et al. (2018), the Cronbach's alpha value of 0.6 is acceptable for the research. As AUT has the lowest Cronbach's alpha value of 0.555 which is considered as poor reliability, the study will remove this variable to maintain the validity of the structural model.

4.3 Inferential Analysis

4.3.1 Pearson's Correlation Coefficient

Table 4.6: Correlation's Results

		REL	COM	PU	PEOU	BIU	AIU	AP
REL	Pearson Correlation	1	.352**	.580**	.458**	.534**	.375**	.362**
	Sig. (2-tailed)		<.001	<.001	<.001	<.001	<.001	<.001
	N	202	202	202	202	202	202	202
COM	Pearson Correlation	.352**	1	.340**	.739**	.576**	.809**	.798**
	Sig. (2-tailed)	<.001		<.001	<.001	<.001	<.001	<.001
	N	202	202	202	202	202	202	202
PU	Pearson Correlation	.580**	.340**	1	.696**	.721**	.559**	.597**
	Sig. (2-tailed)	<.001	<.001		<.001	<.001	<.001	<.001
	N	202	202	202	202	202	202	202
PEOU	Pearson Correlation	.458**	.739**	.696**	1	.693**	.820**	.817**
	Sig. (2-tailed)	<.001	<.001	<.001		<.001	<.001	<.001
	N	202	202	202	202	202	202	202
BIU	Pearson Correlation	.534**	.576**	.721**	.693**	1	.631**	.619**
	Sig. (2-tailed)	<.001	<.001	<.001	<.001		<.001	<.001
	N	202	202	202	202	202	202	202
AIU	Pearson Correlation	.375**	.809**	.559**	.820**	.631**	1	.840**
	Sig. (2-tailed)	<.001	<.001	<.001	<.001	<.001		<.001

	N	202	202	202	202	202	202	202
AP	Pearson Correlation	.362**	.798**	.597**	.817**	.619**	.840**	1
	Sig. (2-tailed)	<.001	<.001	<.001	<.001	<.001	<.001	
	N	202	202	202	202	202	202	202

Note: **. Correlation is significant at the 0.01 level (2-tailed).

Source: Author's Own Elaboration

Table 4.7 demonstrates the relationship between the dependent, mediating and independent variables. Within the primary indicators of BIU, PU was found to have a stronger relationship (0.721) than PEOU (0.693). Thus, it can be explained the usefulness of the AI tools is an essential factor for students to engage with AI. In terms of SDT, a stronger relationship was found to exist between COM and BIU (0.576) than REL (0.534). Moreover, there is also a strong relationship between BIU and AIU (0.631). However, the strongest relationship in the result was found between AIU and AP, consisting of a very strong positive correlation, with a value of 0.840. This shows that students who utilise AI tools in their learning process tend to achieve higher perceived academic performance.

4.3.2 Multiple Linear Regression

Table 4.8: Multiple Linear Regression Analysis (Behavioural Intention to Use AI)

Variables	Coefficients	t	Sig	VIF
REL	.092	1.735	.084	1.583
COM	.342	4.993	<.001	2.636
PU	.531	7.534	<.001	2.792
PEOU	.028	.318	.751	4.380
F-Value	91.008			
F-sig	<.001			
R Square	.649			
Adjusted R Square	.642			
a. Dependent Variable: Behavioural Intention to Use AI (BIU)				

Source: Author's Own Elaboration

Table 4.8 shows that 64.9% ($R^2 = 0.649$) of the variance in BIU can be explained by REL, COM, PU and PEOU. Among these independent variables, PU has the most significant impact ($\beta = 0.531, p < 0.001$) on BIU, followed by COM ($\beta = 0.342$, $p < 0.001$). This indicates that the intention to use AI is significantly higher among those who view AI as highly functional and able to enhance their ability. In contrast, REL (0.084) and PEOU (0.751) are not significant. Moreover, the VIF for all variables is below 5, there is no issue with multicollinearity.

Table 4.9: Multiple Linear Regression Analysis (AI Usage)

Variables	Coefficients	t	Sig	VIF
BIU	.631	11.503	<.001	1.000
F-Value	132.314			
F-sig	<.001			
R Square	.398			
Adjusted R Square	.395			
a. Dependent Variable: AI Usage (AIU)				

Source: Author's Own Elaboration

Table 4.9 shows that 39.8% ($R^2 = 0.398$) of the variance in AIU can be explained by BIU. Other than that, the model is significant as $p < 0.001$. BIU has a strong positive coefficient (β=0.631) with a highly significant t-statistics of 11.503. This demonstrates a direct relationship: when a student's intention to use AI increases, their AI usage will also increase. In addition, the VIF value of 1.000 exhibits that there is no multicollinearity issue.

Table 4.10: Multiple Linear Regression Analysis (Perceived Academic Performance)

Variables	Coefficients	t	Sig	VIF
AIU	.840	21.902	<.001	1.000
F-Value	479.717			
F-sig	<.001			
R Square	.706			
Adjusted R Square	.704			
a. Dependent Variable: Perceived Academic Performance (AP)				

Source: Author's Own Elaboration

Table 4.10 shows that 70.6% ($R^2 = 0.706$) of the variance in AIU can be explained by AIU. There is a very strong positive relationship between these two variables (β = 0.840, p < 0.001). Other than that, the t-statistics is significantly high which proves that AI usage is a strong predictor of AP. Finally, the VIF value of 1.000 also indicates that there is no multicollinearity issue in this model.

4.4 Major Findings

Table 4.11: Summary of Hypotheses Testing Results

Hypotheses	Path	p-value	Hypotheses Results
Hypotheses 2	COM→BIU	<.001	Supported
Hypotheses 3	REL→BIU	0.084	Supported
Hypotheses 4	PU→BIU	<.001	Supported
Hypotheses 5	PEOU→BIU	0.751	Not Supported
Hypotheses 6	BIU→AIU	<.001	Supported
Hypotheses 7	AIU→AP	<.001	Supported

Source: Author's Own Elaboration

4.4.1 Hypotheses 2

H_0: There is no relationship between competence (COM) and behavioural intention to use AI (BIU)

H_A: There is a relationship between competence (COM) and behavioural intention to use AI (BIU)

There is a significant relationship between competence (COM) and behavioural intention to use AI (BIU) as the p-value (<.001) is less than 0.05. Thus, we reject *H_0*. This linkage is supported by Alharbi (2023) and Yuniawan et al. (2025), when people feel competent while using AI, their intention to adopt AI tools will increase. The fulfilment of the competence could help students to experience a sense of achievement. This achievement drives their intention to use AI continuously in future.

4.4.2 Hypotheses 3

H_0: There is no relationship between relatedness (REL) and behavioural intention to use AI (BIU)

H_A: There is a relationship between relatedness (REL) and behavioural intention to use AI (BIU)

There is a significant relationship between relatedness (REL) and behavioural intention to use AI (BIU) as the p-value (0.084) is more than 0.05. Thus, we do not reject *H_0*. This relationship is supported by Surachmi et al. (2025) and Alharbi (2023), when student feels that AI is a bridge to better engage with their peers, their intention to use it will increase. By using these AI tools to clarify complex concepts or brainstorm ideas, students feel more confident participating in group discussions.

4.4.3 Hypotheses 4

H_0: There is no relationship between perceived usefulness (PU) and behavioural intention to use AI (BIU)

H_A: There is a relationship between perceived usefulness (PU) and behavioural intention to use AI (BIU)

There is a significant relationship between perceived usefulness (PU) and behavioural intention to use AI (BIU) as the p-value (<.001) is less than 0.05. Thus, we reject H_0. This finding is aligned with the research by Duong et al. (2023) and Esiyok et al. (2024). When students feel that AI tools can enhance their productivity. In this fast-paced learning environment, the AI tools can help students to organise the learning materials, improve the quality of group assignments, etc. It assists students in juggling with multiple complicated tasks at the same time and give immediate feedback.

4.4.4 Hypotheses 5

H_0: There is no relationship between perceived ease of use (PEOU) and behavioural intention to use AI (BIU)

H_A: There is a relationship between perceived ease of use (PEOU) and behavioural intention to use AI (BIU)

There is no significant relationship between perceived ease of use (PEOU) and behavioural intention to use AI (BIU) as the p-value (0.751) is more than 0.05. Thus, we fail to reject H_0. This negative relationship can be further supported by Gong and Mao (2026). They mentioned that perceived ease of use does not directly influence students' intention to use AI. This is probably because AI is has become standardised as students can see integrated AI in software like Microsoft 365, WhatsApp, etc. Therefore, student no longer think about the ease of using AI because it is already an integral part of their academic life. As a result, ease has become a baseline rather than a motivation factor.

4.4.5 Hypotheses 6

H_0: There is no relationship between behavioural intention to use AI (BIU) and AI usage (AIU)

H_A: There is a relationship between behavioural intention to use AI (BIU) and AI usage (AIU)

There is a significant relationship between behavioural intention to use AI (BIU) and AI usage (AIU) as p-value (<.001) is less than 0.05. Thus, we reject *H_0*. According to Esiyok et al. (2024), the intention to use AI has positive effect on AI usage. Other than that, Tandon et al. (2024) also mentioned that the intention to use AI facilitate the AI implementation. In an environment where deadlines are the only constant, the intention to use AI is not driven by curiosity, but by the survivalist need to be efficient in order to meet university's strict requirements. The intention will immediately turn into actual use to reduce the academic and psychological burden.

4.4.6 Hypotheses 7

H_0: There is no relationship between AI usage (AIU) and perceived academic performance (AP)

H_A: There is a relationship between AI usage (AIU) and perceived academic performance (AP)

There is a significant relationship between AI usage (AIU) and perceived academic performance (AP) as p-value (<.001) is less than 0.05. Thus, we reject

H_0. According to Dahri et al. (2025) and Khalkho et al. (2024), students will enhance their academic performance when they use AI power tools. This is because AI can simplify the complicated learning materials into more understandable way for student. Moreover, AI always support students 24/7, students can ask unlimited questions they want.

4.5 Conclusion

This chapter has interpreted both quantitative and qualitative findings. It revealed the perceptions from the students' motivation to use AI and also their perceived academic performance.

CHAPTER 5: CONCLUSION AND IMPLICATIONS

5.0 Introduction

Chapter 5 summarises the findings and answers the research questions. It also mentions the practical implications, limitations and future research recommendations of this study.

5.1 Discussion of Research Questions

5.1.1 Factors Influencing Students' Intention to Use AI (RQ1)

The qualitative analysis revealed that the behavioural intention to use AI (BIU) among student is largely influenced by the functionality and their sense of efficacy of the tools used. Specifically, perceived usefulness (PU) is the strongest predictor, with the value of $\beta = 0.531$, $p < 0.001$, followed by competence (COM) and relatedness (REL) with the value of $\beta = 0.342$, $p < 0.001$ and $\beta = 0.092$, $p < 0.10$ respectively. This demonstrates that students are highly motivated to engage with AI when they found that AI actually help them to overcome time constraints and enhance their perceived academic performance. In contrast, perceived ease of use (PEOU) did not yield any significant impact. This might indicate that most modern software has been integrated AI with it, it is no longer a motivation factor as it becoming common in today's world. Instead of focusing on the ease of use, students are focusing more on the results. In addition, most conversations between students and AI are totally private, one-to-one interface; therefore, it cannot improve the social interactions of students. In conclusion, competence (COM) and perceived usefulness (PU) will be the motivation factors to students to engage with AI.

5.1.2 The Relationship Between AI Usage and Perceived Academic Performance (RQ 2)

The findings clearly illustrate an influence chain where a students' intention to use AI leads directly to perceived academic performance. It observed behavioural intention to use AI (BIU) a strong predictor to AI usage (AIU), where β=0.631, $p < 0.001$. More importantly, it can be seen in the findings that AI usage (AIU) is a robust predictor of perceived academic performance (AP), where the coefficient is highly positive at β= 0.840, $p < 0.001$. It clearly support that students who make actual AI usage a part of their academic process significantly improve perceived academic performance.

5.1.3 Challenges for AI Adoption (RQ 3)

The qualitative findings demonstrate how students face a multifaceted array of challenges. The interviews determined that there are three main challenges: technical, logical and ethical-institutional barriers. It shows that how structural barriers, such as maintenance, and linguistic inaccuracies (tool responding in an incorrect language) which cause significant disruptions in user experience. Part of the students mentioned that the maximum capacity is also an issue to them as they need to spend money to create a pro version account. Moreover, there is a refined skepticism about relying on AI tools as students experience many logical inaccuracies (including math errors). Most students only possess 50% of confidence on AI tools, although they believe that AI tools enhance their efficiency, they mentioned that common sense and some basic knowledge are required. Finally, there is a critical issue with academic integrity and institutional barriers. Students remain a fear of direct plagiarism while using AI and some academic courses prohibit AI use.

5.2 Practical Implications of the Study

Since the findings indicated that AI usage explaining 70.6% of the variance in perceived academic performance, it is no longer a simple assistant tool for student but a core driver for academic success. Additionally, AI also provides student an opportunity to develop digital literacy that required in future workplaces.

Based on these positive views, the university should assist students on how to use and integrate AI tools in their study accurately instead of merely setting a threshold as a restrictive barrier. The faculty should provide workshops like paraphrasing workshop, prompt engineering workshop, etc. Furthermore, the faculty can also teach students on how to utilise these tools for problem solving, content creation and automated formatting as many organisations also encourage their employees to do so in order to enhance operational efficiency.

For AI developers, they should pay more attention to the logical error and linguistic shift. Developer should prioritise the stability and language consistency to ensure that technical glitches do not disrupt the learning flow. Additionally, they may also consider launching a “pro” access plan for students to eliminate the financial and capacity constraints.

5.3 Limitations of the Study

The primary limitation of this study was the restricted timeframe for data collection, which resulted in a final sample of 202 quantitative respondents and 10 qualitative interviewers. This restriction only allows this study to only focus on one university. Since this study focused specifically on students from Universiti Tunku Abdul Rahman (UTAR). Thus, the findings may only reflect the specific academic culture, digital infrastructure and policies of this institution instead of all universities in Malaysia. The findings might not be fully applicable to other university students or those from different geographical areas and AI regulations. Furthermore, the data was collected at a single point in time, meaning that the study is unable to observe student motivation towards AI over time as their intentions and academic performance might change over the degree cycle. Ultimately, this study is reliance on self-reported data and students' perceptions to measure academic performance instead of using institutional measurement like GPA.

5.4 Recommendations for Future Research

As this research focused on UTAR, future research can conduct comparative studies between private universities or between different areas. Since different institutions have diverse policies, compare them may help researchers to examine whether the strictness of the university will moderate students' motivation to use AI. Other than that, future studies should aim for larger sample size and apply longitudinal approach. This approach can observe students' behaviour towards AI from year 1 to graduation. This will give us a clearer picture of whether AI truly sustain academic success over time or it just levels off. Lastly, future research can integrate the institutional grade to see whether these positive perceptions translate into actual GPA improvement.

5.5 Conclusion

This findings in this research were discussed comprehensively and most variables were proved to be supported. Through both quantitative and qualitative data, we are able to observe that AI usage is the strong predictor of students' perceived academic performance. Moreover, this study also mentioned the limitation of the study and also recommendation for future research to explore a more in-depth information.

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APPENDICES

Appendix 1: Questionnaire

Description:

I am Minnie Ling Yee Lynn, and currently pursuing a Bachelor of Global Economics (Honours) at Universiti Tunku Abdul Rahman (UTAR). As part of my Final Year Project, I am conducting a research study titled "Student Motivation and AI Use: A Pathway to Academic Performance."

This study aims to explore students' motivations for using artificial intelligence (AI) tools, how these motivations translate into the intention to use AI, and how this intention impacts actual AI usage. Additionally, it will examine how AI usage influences academic performance.

Please be assured that all responses you provide will be completely anonymous and confidential. The information collected will be used solely for academic purposes. This survey will take approximately 3 to 5 minutes to complete.

Your participation is entirely voluntary, and I greatly appreciate your honest input. If you have any questions or need further clarification about this study, please don't hesitate to contact me at minnielingyeelynn@1utar.my.

Thank you for your valuable time and participation!

PRIVACY NOTICE

1. This is a Privacy Notice and shall govern UTAR in dealing with protection of personal data. To protect personal data, the Notice may be changed from time to time.
2. Personal Data Protection Act 2010 ("PDPA") came into force on 15 November 2013, therefore 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 data.

A. **What is personal data**
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:
i. Name
ii. Identity card
iii. Place of Birth
iv. Address
v. Examination Result
vi. Education History
vii. Employment History
viii. Medical History
ix. Blood type
x. Race
xi. Religion
xii. Photo

B. **<u>Sources of personal data</u>**
In processing relevant services, UTAR may obtain personal data from various sources such as:
i. Your self

a. from your application forwarded to us. By submitting any application to us, you are hereby confirmed that you have obtained necessary consent for the information to be declared in the application.

b. There could be capturing of images or audios e.g. CCTV for safety and/or recording purposes. A notice will be displayed to the effect.

ii. Third parties

c. UTAR affiliates in competition or survey or research or programmes.

d. your participation with other entities.

e. your guardian, legal representative or guarantor.

f. there may be cross reference of your personal data for loan application or credit reference.

g. previous education institutions or employers.

iii. Websites

h. your IP address is automatically login into our server. Generally, we do not link your IP address to identify each link unless in case of serious breach.

i. you may adjust your browser to disable 'cookies' to prevent storage of certain information in your system.

C. **Purpose of personal data:**

In servicing our obligations, the purposes for which your personal data may be used are inclusive but not limited to:

i. For assessment of any application to UTAR
ii. For processing any benefits and services
iii. For communication purposes
iv. For advertorial and news
v. For general administration and record purposes
vi. For enhancing the value of education
vii. For educational and related purposes consequential to UTAR
viii. For replying any responds to complaints and enquiries
ix. For the purpose of our corporate governance
x. For consideration as a guarantor for UTAR staff/ student applying for his/her scholarship/ study loan

D. **Disclosure of personal data:**

i. UTAR is under legal obligation to secure and protect confidential information including but not limited to personal data prior and after PDPA and it is our continuous and existing policy to do so.

ii. In order to be effective in providing continuous service, certain disclosure needs to be exercised. 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.

iii. In processing your welfare and/or providing our services, it is very important to transmit or share personal information to third parties, including but not limited to:

a. insurance company for processing insurance claims

b. financial institutions for payment of financial rewards eg scholarship, loan, allowance, salary

c. entities/affiliates for any loan/scholarship award or recognition and education-related activities

d. your authorized third parties

e. your guardian or legal representative or guarantor

f. credit rating agency for credit reference in loan related application

g. enforcement regulatory and governmental agencies or by any order of court or to meet obligations to authorities

iv. Your data may be shared when required by laws and when disclosure is necessary to comply with applicable laws.

E. **<u>Retention of personal data</u>**
Any personal information shall be retained by UTAR in order to serve the above purposes and as required by relevant laws and shall be destroyed and/or deleted in accordance with our retention policy applicable for us in the event such information is no longer required.

F. **<u>Our strict privacy policy</u>**
i. 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.

ii. UTAR takes a high stand that protection of personal rights is well-established long before the introduction of PDPA. PDPA now serves as an apparent Act to protect and a defined tool to provide transparency and give public awareness in how personal data is dealt.

iii. Subject to relevant applicable laws, sensitive personal data shall only be disclosed upon your express consent from your self.

G. **<u>Access to your personal data</u>**
You may access and update your personal data by writing to us at rgo@utar.edu.my (Attention: Ms Loh Siaw Yien). We may require further details or confirmations if necessary.

H. **<u>Consent is fundamental</u>**
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.

I. **Withdrawal of consent**

i. You may withdraw consent at any time by writing to us. We may require further details or confirmations if necessary.

ii. 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 reward or to assist you in respect of the purposes and/or for any other purposes related to the purpose.

J. **Dual Version**

The Privacy Notice shall be in English and Malay. In the event of inconsistency, English version shall prevail.

Survey Informed Consent:

By proceeding with this survey, you are voluntarily agreeing to participate in a research study for a Final Year Project (FYP). The purpose of this study is to explore student motivation to use AI tools and how it influences academic performance. Your responses will be kept confidential, and all data collected will be used solely for research purposes related to this project.

- I agree to participate in this study.
- I do not agree to participate in this study.

Section A: Demographic Questions

1. What's your gender?

- Female
- Male

2. What year are you currently in?

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

3. Have you ever used AI tools (e.g., ChatGPT, AI-based research tools) in your studies?

- Yes
- No

4. What types of AI tools have you used for your academic work?

- ChatGPT
- Perplexity
- Gemini
- DeepSeek
- Copilot
- Other (please specify):

5. How frequently do you use AI tools for your academic tasks?

- Daily
- Weekly
- Monthly
- Rarely
- Never

Section B: Motivation to Use AI (SDT & TAM)

Autonomy (AUT)

Kindly rate the following statements on <u>Autonomy</u> from (1) Strongly Disagree to (5) Strongly Agree

Questions	1	2	3	4	5
1. I decide how I use AI tools in my studies.					
2. I feel pressured when I use AI tools in my studies.					
3. I am free to express my ideas on how I use AI tools.					
4. I follow my lecturer's guidance on how to use AI tools.					
5. I care my feelings when I use AI tools in my studies.					
6. I can use AI tools in ways that suit my learning style.					
7. I have opportunities to decide how I want to use AI tools.					

Competence (COM)

Kindly rate the following statements on <u>Competence</u> from (1) Strongly Disagree to (5) Strongly Agree

Questions	1	2	3	4	5
1. I feel very competent when using AI tools in my studies.					
2. My peers tell me I am good in using AI tools for my studies.					
3. I have learned new skills by using AI tools.					
4. I feel a sense of accomplishment when I use AI tools in my studies.					
5. I have many chances to show my capabilities in using AI tools.					
6. I feel capable when I use AI tools for learning tasks.					

Relatedness (REL)

Kindly rate the following statements on <u>Relatedness</u> from (1) Strongly Disagree to (5) Strongly Agree

Questions	1	2	3	4	5
1. I feel accepted by my peers when I use AI tools in my studies.					
2. I feel valued when participating on using AI tools.					
3. I do not feel ignored when I use AI tools.					
4. I feel it is important to use AI tools in my studies.					

Perceived Usefulness (PU)

Kindly rate the following statements on <u>Perceived Usefulness</u> from (1) Strongly Disagree to (5) Strongly Agree

Questions	1	2	3	4	5
1. Using AI tools helps me complete my assignments more quickly.					
2. Using AI tools helps improve my academic performance.					
3. AI tools make me a more productive student.					
4. AI tools make me easier to manage my studies.					
5. I find AI tools useful for my studies.					
6. AI tools increase my effectiveness as a student.					

Perceived Ease of Use (PEOU)

Kindly rate the following statements on <u>Perceived Ease of Use</u> from (1) Strongly Disagree to (5) Strongly Agree

Questions	1	2	3	4	5
1. Learning how to use AI tools is easy for me.					
2. I find it easy to get AI tools to do what I need for my studies.					
3. I can interact with AI tools easily.					
4. I find AI tools flexible enough for my studies.					
5. It is easy for me to become skilful at using AI tools.					
6. AI tools are easy for me to use.					

Section C: Behavioural Intention to Use AI (BIU)

Kindly rate the following statements on <u>Behavioural Intention to Use AI</u> from (1) Strongly Disagree to (5) Strongly Agree

Questions	1	2	3	4	5
1. I intend to use AI tools for my learning in future courses.					
2. I expect myself to continue to use AI tools in my studies.					
3. I plan to use AI tools whenever it is available for my studies.					
4. I intend to keep using AI tools rather than stop using them.					
5. I prefer to use AI tools instead of other methods.					
6. I intend to use AI tools for my studies instead of stop using it.					

Section D: AI Usage (AIU)

Kindly rate the following statements on <u>AI Usage</u> from (1) Strongly Disagree to (5) Strongly Agree

Questions	1	2	3	4	5
1. I use AI tools for general learning purposes					
2. I use AI tools for searching for academic literature					
3. I use AI tools for writing assignments					
4. I use AI tools for working on long essays, theses, or major projects					
5. I use AI tools for writing term papers					
6. I use AI tools for doing undergraduate project work					
7. I use AI tools for coding or generating commands					
8. I use AI tools for preparing PowerPoint slides					
9. I use AI tools for writing or drafting academic articles					

Section E: Academic Performance (AP)

Kindly rate the following statements on <u>Academic Performance</u> from (1) Strongly Disagree to (5) Strongly Agree

Questions	1	2	3	4	5
1. AI tools have improved my academic performance.					
2. AI tools have helped me improve my problem-solving and critical thinking skills.					
3. AI tools help me to achieve higher academic performance.					
4. I see improvement in my academic performance because I use AI tools.					
5. AI tools have helped me be more successful in my studies.					
6. Overall, AI tools have positive influences on my academic performance.					

Appendix 2: Interview Questions

INTERVIEW QUESTIONS

Section A: Background

1. What kind of AI tools do you commonly use?
2. What are your purposes to use AI tools?
3. What are your motivation factors to use AI tools in your studies?

Section B: Factors influencing willingness to use AI (RQ 1)

4. Do AI tools allow you to approach your learning in your own way? How?
5. Can you use AI tools freely in your studies? Share your experiences.
6. How confident are you in using AI tools to complete your academic tasks?
7. Do you think you become more competent in your studies after using AI tools?
8. In your opinion, how useful are AI tools for your learning or coursework? Why do you say so?
9. Do you think it is easy to use AI tools? Share your experience.
10. How easy or difficult is it for you to learn and use AI tools for your studies?
11. What factors encourage you to actually open and use an AI tool when doing an assignment or studying?

Section D: AI Usage and Academic Performance

12. From your experience, how has using AI tools influenced your academic performance?
13. Can you describe how AI tools affect your academic performance? (Can be positive or negative)

Section E: Challenges and Barriers in Using AI

14. What are the main challenges or difficulties you face when using AI tools for your studies?
15. Have you ever received unclear or incorrect answers from AI tools? How did you handle that?
16. How aware are you of the capabilities of generative AI tools, such as ChatGPT, in supporting your academic tasks?

Appendix 2: Official Ethical Approval Letter

UNIVERSITI TUNKU ABDUL RAHMAN
Wholly Owned by UTAR Education Foundation (Company No. 578227-M)

Re: U/SERC/78-678/2026

19 January 2026

Dr Aye Aye Khin
Head, Department of Economics
Faculty of Accountancy and Management
Universiti Tunku Abdul Rahman
Jalan Sungai Long
Bandar Sungai Long
43000 Kajang, Selangor.

Dear Dr Aye Aye Khin,

Ethical Approval For Research Project/Protocol

We refer to your application for ethical approval for your students' research project from Bachelor of Economics (Honours) Global Economics programme enrolled in course UKEZ3026. We are pleased to inform you that the application has been approved under Expedited Review.

The details of the research projects are as follows:

No.	Research Title	Student's Name	Supervisor's Name	Approval Validity
1.	Choosing Careers in a Gig World: Insights from Malaysian Final Year Students	Yap Chen Yan	Mr Low Choon Wei	19 January 2026 - 18 January 2027
2.	Student Motivation and AI Use: A Pathway to Academic Performance	Minnie Ling Yee Lynn		
3.	Factors Influencing Career Adaptability Among University Students in Malaysia	Ng Shinjou		

The conduct of this research is subject to the following:

(1) The participants' informed consent be obtained prior to the commencement of the research;

(2) Confidentiality of participants' personal data must be maintained; and

(3) Compliance with procedures set out in related policies of UTAR such as the UTAR Research Ethics and Code of Conduct, Code of Practice for Research Involving Humans and other related policies/guidelines.

(4) Written consent be obtained from the institution(s)/company(ies) in which the physical or/and online survey will be carried out, prior to the commencement of the research.

Kampar Campus : Jalan Universiti, Bandar Barat, 31900 Kampar, Perak Darul Ridzuan, Malaysia
Tel: (605) 468 8888 **Fax**: (605) 466 1313
Sungai Long Campus : Jalan Sungai Long, Bandar Sungai Long, Cheras, 43000 Kajang, Selangor Darul Ehsan, Malaysia
Tel: (603) 9086 0288 **Fax**: (603) 9019 8868
Website: www.utar.edu.my

Should the students collect personal data of participants in their studies, please have the participants sign the attached Personal Data Protection Statement for records.

Thank you.

Yours sincerely,

Professor Dr Zuraidah Abd Manaf
Chairman
UTAR Scientific and Ethical Review Committee

c.c Dean, Faculty of Accountancy and Management

Kampar Campus : Jalan Universiti, Bandar Barat, 31900 Kampar, Perak Darul Ridzuan, Malaysia
Tel: (605) 468 8888 **Fax**: (605) 466 1313
Sungai Long Campus : Jalan Sungai Long, Bandar Sungai Long, Cheras, 43000 Kajang, Selangor Darul Ehsan, Malaysia
Tel: (603) 9086 0288 **Fax**: (603) 9019 8868
Website: www.utar.edu.my

Appendix 3: SPSS Output

Appendix 3.1: Frequency Table

Gender

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	122	60.4	60.4	60.4
	2	80	39.6	39.6	100.0
	Total	202	100.0	100.0	

Programme of Study

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	71	35.1	35.1	35.1
	2	22	10.9	10.9	46.0
	3	13	6.4	6.4	52.5
	4	70	34.7	34.7	87.1
	5	26	12.9	12.9	100.0
	Total	202	100.0	100.0	

Year of Study

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	34	16.8	16.8	16.8
	2	83	41.1	41.1	57.9
	3	77	38.1	38.1	96.0
	4	8	4.0	4.0	100.0
	Total	202	100.0	100.0	

Have you ever used AI tools in your studies?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	202	100.0	100.0	100.0

What types of AI tools have you used for your academic work?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	27	13.4	13.4	13.4
	2	55	27.2	27.2	40.6
	3	106	52.5	52.5	93.1
	4	9	4.5	4.5	97.5
	5	5	2.5	2.5	100.0
	Total	202	100.0	100.0	

How frequently do you use AI tools for your academic tasks?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	134	66.3	66.3	66.3
	2	67	33.2	33.2	99.5
	3	1	.5	.5	100.0
	Total	202	100.0	100.0	

Appendix 3.2: Descriptive Statistics

Descriptive Statistics

	N Statistic	Minimum Statistic	Maximum Statistic	Mean Statistic	Std. Deviation Statistic	Skewness Statistic
AUT	202	1.57	5.00	4.3522	.42276	-1.999
REL	202	1.50	5.00	4.3874	.47839	-1.925
COM	202	1.00	5.00	4.0239	.84256	-1.034
PU	202	1.00	5.00	4.5446	.43218	-3.398
PEOU	202	1.00	5.00	4.3721	.49375	-1.721
BIU	202	1.00	5.00	4.4183	.47846	-2.505
AIU	202	1.00	5.00	4.2778	.57112	-1.293
AP	202	1.00	5.00	4.3383	.56743	-1.388
Valid N (listwise)	202					

Descriptive Statistics

	Skewness	Kurtosis	
	Std. Error	Statistic	Std. Error
AUT	.171	9.185	.341
REL	.171	6.943	.341
COM	.171	.020	.341
PU	.171	23.201	.341
PEOU	.171	9.574	.341
BIU	.171	14.848	.341
AIU	.171	4.261	.341
AP	.171	4.625	.341
Valid N (listwise)			

Appendix 3.3: Cronbach's Alpha

Scale: AUT

Case Processing Summary

		N	%
Cases	Valid	202	100.0
	Excluded[a]	0	.0
	Total	202	100.0

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

Reliability Statistics

Cronbach's Alpha	N of Items
.555	7

Scale: REL

Case Processing Summary

		N	%
Cases	Valid	202	100.0
	Excluded[a]	0	.0
	Total	202	100.0

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

Reliability Statistics

Cronbach's Alpha	N of Items
.682	4

Scale: COM

Case Processing Summary

		N	%
Cases	Valid	202	100.0
	Excluded[a]	0	.0
	Total	202	100.0

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

Reliability Statistics

Cronbach's Alpha	N of Items
.928	6

Scale: PU

Case Processing Summary

		N	%
Cases	Valid	202	100.0
	Excluded[a]	0	.0
	Total	202	100.0

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

Reliability Statistics

Cronbach's Alpha	N of Items
.826	6

Scale: PEOU

Case Processing Summary

		N	%
Cases	Valid	202	100.0
	Excluded[a]	0	.0
	Total	202	100.0

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

Reliability Statistics

Cronbach's Alpha	N of Items
.782	6

Scale: BIU

Case Processing Summary

		N	%
Cases	Valid	202	100.0
	Excluded[a]	0	.0
	Total	202	100.0

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

Reliability Statistics

Cronbach's Alpha	N of Items
.783	6

Scale: AIU

Case Processing Summary

		N	%
Cases	Valid	202	100.0
	Excluded[a]	0	.0
	Total	202	100.0

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

Reliability Statistics

Cronbach's Alpha	N of Items
.892	9

Scale: AP

Case Processing Summary

		N	%
Cases	Valid	202	100.0
	Excluded[a]	0	.0
	Total	202	100.0

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

Reliability Statistics

Cronbach's Alpha	N of Items
.823	6

Appendix 3.4: Pearson's Correlation

Correlations

		AUT	REL	COM	PU	PEOU	BIU
AUT	Pearson Correlation	1	.692**	.348**	.559**	.540**	.602**
	Sig. (2-tailed)		<.001	<.001	<.001	<.001	<.001
	N	202	202	202	202	202	202
REL	Pearson Correlation	.692**	1	.352**	.580**	.458**	.534**
	Sig. (2-tailed)	<.001		<.001	<.001	<.001	<.001
	N	202	202	202	202	202	202
COM	Pearson Correlation	.348**	.352**	1	.340**	.739**	.576**
	Sig. (2-tailed)	<.001	<.001		<.001	<.001	<.001
	N	202	202	202	202	202	202
PU	Pearson Correlation	.559**	.580**	.340**	1	.696**	.721**
	Sig. (2-tailed)	<.001	<.001	<.001		<.001	<.001
	N	202	202	202	202	202	202
PEOU	Pearson Correlation	.540**	.458**	.739**	.696**	1	.693**
	Sig. (2-tailed)	<.001	<.001	<.001	<.001		<.001
	N	202	202	202	202	202	202
BIU	Pearson Correlation	.602**	.534**	.576**	.721**	.693**	1
	Sig. (2-tailed)	<.001	<.001	<.001	<.001	<.001	
	N	202	202	202	202	202	202
AIU	Pearson Correlation	.507**	.375**	.809**	.559**	.820**	.631**
	Sig. (2-tailed)	<.001	<.001	<.001	<.001	<.001	<.001
	N	202	202	202	202	202	202
AP	Pearson Correlation	.406**	.362**	.798**	.597**	.817**	.619**
	Sig. (2-tailed)	<.001	<.001	<.001	<.001	<.001	<.001
	N	202	202	202	202	202	202

Correlations

		AIU	AP
AUT	Pearson Correlation	.507**	.406**
	Sig. (2-tailed)	<.001	<.001
	N	202	202
REL	Pearson Correlation	.375**	.362**
	Sig. (2-tailed)	<.001	<.001
	N	202	202
COM	Pearson Correlation	.809**	.798**
	Sig. (2-tailed)	<.001	<.001
	N	202	202
PU	Pearson Correlation	.559**	.597**
	Sig. (2-tailed)	<.001	<.001
	N	202	202
PEOU	Pearson Correlation	.820**	.817**
	Sig. (2-tailed)	<.001	<.001
	N	202	202
BIU	Pearson Correlation	.631**	.619**
	Sig. (2-tailed)	<.001	<.001
	N	202	202
AIU	Pearson Correlation	1	.840**
	Sig. (2-tailed)		<.001
	N	202	202
AP	Pearson Correlation	.840**	1
	Sig. (2-tailed)	<.001	
	N	202	202

Appendix 3.5: Multiple Regression

Coefficients[l]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance
1	(Constant)	.439	.231		1.902	.059	
	REL	.092	.053	.092	1.735	.084	.632
	COM	.194	.039	.342	4.993	<.001	.379
	PU	.588	.078	.531	7.534	<.001	.358
	PEOU	.027	.086	.028	.318	.751	.228

Coefficients[a]

Model		Collinearit y Statistics VIF
1	(Constant)	
	REL	1.583
	COM	2.636
	PU	2.792
	PEOU	4.380

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearit y Statistics Tolerance
1	(Constant)	.950	.291		3.264	.001	
	BIU	.753	.065	.631	11.503	<.001	1.000

Coefficients[a]

Model		Collinearit y Statistics VIF
1	(Constant)	
	BIU	1.000

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearit y Statistics Tolerance
1	(Constant)	.768	.164		4.668	<.001	
	AIU	.835	.038	.840	21.902	<.001	1.000

Coefficients[a]

Model		Collinearit y Statistics VIF
1	(Constant)	
	AIU	1.000