EXAMINING THE DETERMINANTS OF AI DEPENDENCY ON GENERATIVE ARTIFICIAL INTELLIGENCE (GENAI) AMONG UNDERGRADUATES IN A MALAYSIAN PRIVATE UNIVERSITY

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APRIL 2026

PREFACE

This research study was carried out as part of the requirements for completing the Bachelor of Business Administration (Honours) at a private Malaysian university. The title of this research is "Examining the Determinants of AI Dependency on Generative Artificial Intelligence (GenAI) Among Undergraduates in a Malaysian Private University." This topic was selected in response to the quick and extensive adoption of GenAI technologies in a variety of sectors, especially higher education, where their effect on students' academic engagement and learning behaviours has become more noticeable.

The growing integration of GenAI in academic settings has raised potential opportunities and concerns. The growing prominence of GenAI in academic environments has raised potential opportunities and issues. Although these AI tools provide substantial benefits in terms of efficiency and information accessibility, an over-reliance on them raises serious concerns regarding students' capacity for independent thinking, critical reasoning, and long-term academic growth. Understanding the psychological, technical, and social elements that contribute to AI dependency is both relevant and essential, as undergraduate students will make up Malaysia's future workforce, a country aiming for a knowledge-based economy.

This study examines six independent variables, which are academic self-efficacy, academic stress, performance expectancy, academic workload, time pressure, and social influence, and investigates their effects on AI dependency among undergraduates. The findings of this study will serve as a meaningful reference for university administrators, educators, and policymakers in developing strategies that promote responsible and balanced GenAI usage among undergraduate students in Malaysia.

ABSTRACT

This study explores the determinants of AI dependency on generative artificial intelligence (GenAI) among undergraduate students in a Malaysian private university. With the growing integration of GenAI tools in higher education, concerns have emerged regarding their influence on students' learning behaviours, critical thinking abilities, and level of academic engagement. Based on the Unified Theory of Acceptance and Use of Technology (UTAUT) and Social Cognitive Theory (SCT), The study focuses on six independent variables which are academic self-efficacy, academic stress, performance expectancy, academic workload, time pressure, and social influence, and examines their effects on AI dependency.

The study focuses on a private university which is UTAR in both campuses which are Kampar and Sungai Long. In this research, there are 388 respondents collected for questionnaires at both campuses successfully. The data analysed using descriptive statistics, reliability and normality tests, as well as Pearson Correlation Coefficient Analysis and Multiple Regression Analysis via Statistical Package for the Social Sciences (SPSS) version 31.

The results show that academic self-efficacy is significant negative relationship with AI dependency, while academic stress is non-significant direct effect to AI dependency. Performance expectancy, academic workload, time pressure, and social influence are significant positive relationship with AI dependency. Among these variables, time pressure was identified as the strongest predictors, indicating that students tend to rely more heavily on GenAI when facing tight deadlines and when they perceive the technology as effective in improving academic performance. These findings demonstrate that both psychological factors and situational pressures play a significant role in shaping students' dependency on AI tools. Lastly, the research has presented a summary of major findings, implications of the study, limitations and recommendations.

Keywords: AI Dependency, Academic Self-Efficacy, Academic Stress, Performance Expectancy, Academic Workload, Time Pressure, Social Influence

Subject Area: HM1106-1171 Social Behavior

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LIST OF ABBREVIATIONS

ANOVA	Analysis of Variance
AID	AI Dependency
AS	Academic Stress
ASE	Academic Self-Efficacy
AW	Academic Workload
GenAI	Generative Artificial Intelligence
PE	Performance Expectancy
SCT	Social Cognitive Theory
SI	Social Influence
SPSS	Statistical Package for the Social Sciences
TP	Time Pressure
UTAR	Universiti Tunku Abdul Rahman
UTAUT	Unified Theory of Acceptance and Use of Technology

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CHAPTER 1: RESEARCH OVERVIEW

1.0 Introduction

The rapid growth of Generative Artificial Intelligence (GenAI) has significantly changed how undergraduates approach their academic work. While GenAI offers many benefits in terms of efficiency and productivity, its increasing use has also brought up concerns about AI Dependency among students. This chapter presents the research background, problem statement, research objectives, research questions, hypotheses, significance of the study, and the overall organisation of the thesis.

1.1 Research Background

The emergence of Generative Artificial Intelligence (GenAI) stands as one of the most significant technological breakthroughs of the 21st century. It has fundamentally changed how people create, communicate, and learn across nearly every sector of society (Chan & Hu, 2023; Teubner et al., 2023). A clear example is ChatGPT, which was developed by OpenAI and publicly released on 30 November 2022. It has marked a defining moment in the history of human-technology interaction. Within just two months, ChatGPT reached 100 million users worldwide, making it one of the fastest-growing applications in history (He et al., 2024; Hu, 2023; Leiter et al., 2024). Unlike traditional educational technologies, GenAI can create human-like text, summarise notes, help with writing assignments, research, and even coding. It also gives instant and personalised feedback to users (Dwivedi et al., 2023). This powerful combination of accessibility, versatility, and intelligence has made GenAI tools unlike anything previously available to the general public. It has set the stage for their rapid and widespread adoption across multiple domains, including education (Bick et al., 2024; Mittal et al., 2024).

GenAI has quickly become a major part of academic life. A global survey by the Digital Education Council (2024) found that 86% of students now use AI in their studies, with 54% using it weekly and nearly one in four using it daily. In the UK, a 2025 survey of 1,041 undergraduate students showed that 92% were using AI tools, which shows a big jump from 66% in 2024. up sharply from 66% the previous year. Additionally, 88% reported using generative AI for their assessments, compared to just 53% in 2024 (Freeman, 2025). Not only that, this high rate of adoption is further reflected in a large-scale global study, where 23,218 students from 109 countries in early 2024 revealed that students primarily used ChatGPT for brainstorming ideas, summarising texts, and also finding research articles (Ravšelj et al., 2025). Students also leverage GenAI to improve their writing quality, seek explanations for complex concepts, prepare for assessments, and manage the demands of academic tasks more efficiently (Kasneci et al., 2023). These capabilities have made GenAI tools a genuinely attractive academic companion for university students around the world.

The academic community has increasingly recognised the genuine educational benefits GenAI can offer when used thoughtfully. Compared to traditional teaching approaches, it provides scalable, on-demand, and personalised support. It also delivers immediate feedback, offers adaptive explanations, creates tailored learning pathways, helps with problem-solving, and automates routine tasks (Guo et al., 2025; Smolansky et al., 2023; Guo et al., 2024). Beyond improving efficiency, GenAI has been shown to increase student engagement and encourage deeper exploration of subjects (Wood & Moss, 2024). Many students also report that it speeds up time-consuming parts of research, giving them more time for critical thinking and analysis (Wu et al., 2025). Moreover, the integration of GenAI into university classrooms has been found to bridge skill gaps between educational settings and workplace needs, with GenAI tools offering cost-effective learning experiences that support their future careers (Korchak et al., 2025). These benefits help explain why students across different disciplines have warmly embraced GenAI as part of their academic routines.

At the same time, researchers and educators have also begun to observe that GenAI's integration into student life is not without complexity. While students value its ability to boost productivity and academic performance, many also express concerns about academic integrity, overreliance on the tool, and issues around data privacy and security (Chan & Hu, 2023; Jamaluddin et al., 2025). The advantages of GenAI are accompanied by challenges, including concerns about academic integrity due to the potential for misuse in assignments and exams, the risk of overreliance that may hinder critical thinking development, and occasional inaccuracies in responses that can mislead students lacking strong foundational knowledge (Lund et al., 2025; Tlili et al., 2025; Bittle & El-Gayar, 2025). These observations reflect a growing recognition within the academic community that GenAI occupies a dual-edged position in higher education, which is capable of both enriching and complicating the student learning experience.

In Malaysia, the government has been strongly promoting the use of AI and digital technologies in education. The National Artificial Intelligence Roadmap 2021–2025 calls for integrating AI in school and university curricula, training educators, and also building stronger AI capabilities in institutions (Ayuni, 2025). Complementing this, the Digital Education Policy (DEP) launched by the Ministry of Education in 2023 also promotes the use of AI-based learning tools and smart tutoring systems (Jamaluddin et al., 2025). In addition, the establishment of the Ministry of Digital in 2024 and the National AI Office reflects Malaysia's ambition to become a significant player in AI within ASEAN and the global landscape (Sharef, 2025). These policies show that the government sees AI as a central element in the country's educational and economic development.

This supportive environment has clearly accelerated GenAI adoption among Malaysian university students. Local studies confirm that students are actively using ChatGPT and similar tools in their daily academic work. Research has shown that students' belief in ChatGPT's ability to improve their performance strongly influences how much value they see in it and how often they continue using it (Moghavvemi & Jam, 2025). Similar patterns appear among Malaysian healthcare undergraduates, who frequently use the tool to understand complex topics and prepare for assessments (Pallivathukal et al., 2024). Overall, Malaysian students have readily incorporated GenAI into their academic routines, in line with national policy directions.

Within this context, private universities in Malaysia represent a particularly noteworthy setting. Students in these institutions often face demanding programmes, intense academic pressure, heavy assignment loads, and tight deadlines (Zakaria, 2025; Lee, 2025; Tee et al., 2024). These challenges, together with the easy access and perceived usefulness of GenAI tools, have contributed to especially high adoption rates among their undergraduates (Bhuiyan et al., 2025). Undergraduates, in particular, occupy a critical stage of educational development, where they are still building independent learning skills, academic self-confidence, and the cognitive habits that will carry them into professional life (Zakaria, 2025; Lee, 2025; Jia et al., 2025). How they engage with GenAI therefore matters not only for their immediate academic success but also for the long-term quality of Malaysia's future workforce (TalentCorp, 2024; Al-kumaim et al., 2025; Zhang & Pang, 2026). It is against this backdrop that the present study situates its inquiry into the determinants of AI dependency on GenAI among undergraduates in a Malaysian private university.

1.2 Problem Statement

GenAI tools have demonstrated genuine and documented value in higher education settings. A meta-analysis of 35 experimental studies published between 2022 and 2024 found a moderately positive effect of ChatGPT on student learning outcomes, significantly enhancing both cognitive and non-cognitive skills (Wu et al., 2026). Students themselves acknowledge this value and have generally embraced GenAI with awareness of both its strengths and limitations. Research indicates that students increasingly adopt a balanced perspective, valuing AI's utility while remaining mindful of its limitations (Dogaru et al., 2025).

From the outset, it is important to clarify that this study does not view GenAI as an inherently harmful technology, nor does it assume that all student use is problematic. Instead, it recognises that GenAI use exists on a spectrum, ranging from thoughtful, critical, and supplementary engagement to excessive, unreflective, and habitual dependency. Research indicates that the use of GenAI can boost learners' confidence and efficiency, thereby enhancing their self-efficacy; however, frequent use may also result in excessive technological dependency, potentially weakening students' ability to solve problems independently (Zhang & Xu, 2025). It is this spectrum, and what determines where students fall on it, that drives the present study.

AI dependency, in the academic context, refers to a behavioural pattern in which students become excessively and habitually reliant on GenAI tools to complete academic tasks, progressively substituting their own cognitive effort with AI-generated outputs (Zhang et al., 2024). Whether AI dependency is ultimately beneficial or detrimental depends on its degree, the context in which it occurs, and the individual and situational factors that drive it (Goh et al., 2025). Overreliance on GenAI tools can weaken critical thinking and learning motivation, while moderate and structured use may continue to support learning effectively (Tian & Zhang, 2025; Abubakar et al., 2025; Zhai et al., 2024).

Given these dual possibilities, it is essential to move beyond simply describing how much students use GenAI and instead examine the conditions under which use turns into dependency, along with the factors that push students in that direction. Appropriate AI use involves actively engaging with the tool, critically evaluating its outputs, maintaining ethical awareness, transparently acknowledging its use, and preserving one's own agency. In contrast, disuse, misuse, or abuse can undermine these benefits (Sousa & Cardoso, 2025). Understanding what leads students away from appropriate use toward dependency is therefore both theoretically important and practically urgent.

Previous studies have drawn on various theoretical frameworks to explore GenAI-related behaviours among university students. These include the Technology Acceptance Model (TAM) (Davis, 1989), the I-PACE model (Brand et al., 2019), Self-Determination Theory (SDT), and extensions of UTAUT such as UTAUT2 (Venkatesh et al., 2012), each offering valuable but distinct perspectives on why students adopt and engage with GenAI tools. While these frameworks have each contributed meaningfully to the understanding of GenAI-related behaviours, the specific combination of UTAUT and SCT applied together toward AI dependency as a behavioural outcome, rather than adoption intention, remains relatively unexplored in the literature. This study aims to extend existing knowledge by combining UTAUT and SCT into a unified model. It brings together the contextual and situational factors highlighted by UTAUT with the cognitive and motivational factors emphasised by SCT, with AI dependency as the key outcome. This approach responds directly to calls in the literature for more comprehensive theoretical perspectives in higher education technology research (Xue et al., 2024).

In Malaysia, research on GenAI use among university students has grown steadily, with several quantitative studies exploring adoption intentions, usage patterns, and perceptions across different disciplines (Mohamad Mozie et al., 2025; Pallivathukal et al., 2024). Researchers have applied frameworks such as UTAUT and TAM to understand what drives Malaysian students toward adopting GenAI tools, yielding valuable insights into the role of performance expectancy, social influence, and facilitating conditions in shaping adoption behaviour. However, empirical evidence on the specific determinants of AI dependency, as distinct from adoption intention, among Malaysian undergraduates remains scarce. In particular, existing research has yet to examine the combined influence of academic self-efficacy, academic stress, performance expectancy, academic workload, time pressure, and social influence on AI dependency within an integrated UTAUT and SCT framework in a Malaysian private university setting. This study aims to fill that gap.

This study focuses specifically on undergraduates because they represent the student group most susceptible to the academic conditions associated with AI dependency. Unlike postgraduate students who typically possess stronger research skills and greater critical thinking maturity, undergraduates are still in the foundational stage of developing independent academic abilities (Gandhi et al., 2024). They often face heavy coursework, frequent assignments, and competitive grading, which can make them more likely to turn to GenAI as an easy solution that may evolve into dependency without proper guidance (Abbas et al., 2024; Zhong et al., 2024; Liu et al., 2026; Tan et al., 2026). Moreover, the habits formed during undergraduate years tend to carry forward into professional life. Early identification of the factors driving AI dependency is therefore crucial for enabling timely interventions that support balanced AI use and safeguard Malaysia’s long-term human capital development (Zhai et al., 2024; Tan et al., 2026).

Therefore, this study seeks to empirically examine the determinants of AI dependency on GenAI among undergraduates in a Malaysian private university. Specifically, it investigates the influence of academic self-efficacy, academic stress, performance expectancy, academic workload, time pressure, and social influence, underpinned by an integrated UTAUT and SCT theoretical framework. By identifying these determinants, the research aims to create greater awareness of the factors that shape students’ reliance on GenAI, thereby supporting more balanced and responsible use of these tools in higher education.

1.3 Research Objectives

1.3.1 General Objective

This research aims to explore and examine the factors of dependency on Generative Artificial Intelligence (GenAI) among undergraduates in a Malaysian private university. The relationship between six independent variables, which include academic self-efficacy (ASE), academic stress (AS), performance expectancy (PE), academic workload (AW), time pressure (TP), and social influence (SI), will be examined with the dependent variable, the AI dependency (AID), using GenAI.

1.3.2 Specific Objectives

1. To examine whether there is a significant relationship between academic self-efficacy and AI dependency using GenAI among undergraduates in a Malaysian private university.
2. To examine whether there is a significant relationship between academic stress and AI dependency using GenAI among undergraduates in a Malaysian private university.
3. To examine whether there is a significant relationship between performance expectancy and AI dependency using GenAI among undergraduates in a Malaysian private university.
4. To examine whether there is a significant relationship between academic workload and AI dependency using GenAI among undergraduates in a Malaysian private university.
5. To examine whether there is a significant relationship between time pressure and AI dependency using GenAI among undergraduates in a Malaysian private university.
6. To examine whether there is a significant relationship between social influence and AI dependency using GenAI among undergraduates in a Malaysian private university.

1.4 Research Questions

1. Does academic self-efficacy affect the AI dependency using GenAI among undergraduates in a Malaysian private university?

2. Does academic stress affect the AI dependency using GenAI among undergraduates in a Malaysian private university?
3. Does performance expectancy affect the AI dependency using GenAI among undergraduates in a Malaysian private university?
4. Does academic workload affect the AI dependency using GenAI among undergraduates in a Malaysian private university?
5. Does time pressure affect the AI dependency using GenAI among undergraduates in a Malaysian private university?
6. Does social influence affect the AI dependency using GenAI among undergraduates in a Malaysian private university?

1.5 Hypotheses of the Study

H1: There is a significant relationship between academic self-efficacy and AI dependency using GenAI among undergraduates in a Malaysian private university.

H2: There is a significant relationship between academic stress and AI dependency using GenAI among undergraduates in a Malaysian private university.

H3: There is a significant relationship between performance expectancy and AI dependency using GenAI among undergraduates in a Malaysian private university.

H4: There is a significant relationship between academic workload and AI dependency using GenAI among undergraduates in a Malaysian private university.

H5: There is a significant relationship between time pressure and AI dependency using GenAI among undergraduates in a Malaysian private university.

H6: There is a significant relationship between social influence and AI dependency using GenAI among undergraduates in a Malaysian private university.

1.6 Significance of the Study

1.6.1 Theoretical Contribution

This study makes distinct contributions to the theoretical literature on GenAI use and dependency in higher education.

In particular, it extends the application of UTAUT beyond its conventional focus on technology adoption intention toward the less-explored outcome of AI dependency. Most prior applications of UTAUT in education have examined whether and why students intend to adopt or use a technology, treating adoption as the terminal outcome of interest. Studies focusing on AI adoption in education either apply UTAUT without considering students' cognitive preparedness or explore related constructs without integrating them into behavioural intention frameworks (Kim et al., 2025). This study redirects UTAUT's explanatory power toward a more complex and consequential behavioural outcome, which is dependency, thereby broadening the framework's scope and demonstrating its utility beyond adoption research. In doing so, it responds to calls in the literature for UTAUT to be applied across more diverse behavioural outcomes and educational contexts. Recent studies highlight the importance of considering psychological variables to explain complex behaviours such as the repeated and sometimes problematic use of digital tools, and note that the integration of psychological constructs within UTAUT remains insufficiently developed (Tang et al., 2025). This study directly addresses that underdevelopment by integrating SCT's psychological constructs, which are academic self-efficacy and academic stress, into a unified model alongside UTAUT's contextual variables.

In addition, this study contributes a more comprehensive theoretical model of AI dependency than currently exists in the literature. By integrating UTAUT and SCT, this study extends these theoretical foundations into a broader, multi-dimensional model that captures both cognitive-motivational and situational antecedents of AI dependency, and it can offer future researchers a more complete framework to build upon, test, and refine across different educational contexts.

Furthermore, this study extends the theoretical scope by incorporating Social Influence (SI) as a new independent variable in the framework. While existing studies typically highlight individual cognitive and psychological factors, the inclusion of SI acknowledges the powerful impact of peer pressure, academic culture, and social expectations on students' dependency behaviour. This contribution not only enhances the UTAUT model but also provides a more thorough understanding of the causes of AID in higher education.

Lastly, this study contributes empirical evidence from a Malaysian private university undergraduate context, where a setting that is both theoretically meaningful and underrepresented in the AI dependency literature. While UTAUT has been applied among Malaysian higher education students to examine AI adoption in specific disciplines such as history education, its application to AI dependency as a behavioural outcome among undergraduates across disciplines in private universities remains limited. Private universities in Malaysia operate within a distinct institutional environment shaped by competitive academic cultures, market-driven programme structures, and student bodies that are often more technologically engaged than their public university counterparts. Grounding this study in this specific context adds theoretical nuance by demonstrating how UTAUT and SCT constructs operate in a non-Western, developing-country, private higher education environment, thereby enriching the cross-cultural generalisability of both frameworks.

1.6.2 Practical Contribution

Beyond theory, this study carries meaningful implications for stakeholders in the higher education sector.

For universities in Malaysia, the findings can inform the creation of policies, workshops, and support systems that encourage responsible use of GenAI while preventing excessive dependency. By identifying the psychological, academic, and social factors that drive students' reliance on GenAI tools, institutions will be better equipped to strike a balance between technological integration and the preservation of critical thinking and independent learning skills.

For lecturers and academic staff, the results show the pressures and expectations that influence students' academic behaviours. This understanding can assist in designing more effective teaching strategies, student support initiatives, and assessment methods that reduce over-dependence on AI while still leveraging its benefits for learning.

On a broader level, the Ministry of Higher Education (MOHE) may use the insights to improve national guidelines on AI adoption in higher education. This can ensure that innovation and digital transformation are aligned with the long-term goals of academic integrity and student development.

Finally, for students themselves, the research offers valuable awareness of how academic stress, workload, time constraints, and social influence shape their reliance on AI. This knowledge can help them develop healthier study practices, manage time more effectively, and also cultivate a balanced approach to using GenAI for academic purposes.

1.7 Chapter Layout

Chapter 1: Research Overview

Highlights the research background, research objectives and questions, hypotheses, problem statement, significance of the study, chapter layout, and conclusion.

Chapter 2: Literature Review

Discussion of the underlying theory, relevant theoretical framework and model, proposed research conceptual framework, review of literature, and hypotheses development.

Chapter 3: Research Methodology

Discussion of research design, sampling design, research instrument, data collection methods, data processing, measurement scales, and data analysis.

Chapter 4: Data Analysis

The survey was conducted using Google Forms, and the data collected will be interpreted through SPSS software.

Chapter 5: Conclusion and Discussion

Summarise the results and findings, the discussion of theoretical and managerial implications, limitations of the research study, and recommendations for future study.

1.8 Chapter Summary

This chapter provided an overview of the research on the determinants of AI Dependency on Generative Artificial Intelligence (GenAI) among undergraduates in a Malaysian private university. It covered the research background, problem statement, research objectives, research questions, hypotheses, and the significance of the study. The following chapter will review the relevant literature and develop the conceptual framework.

CHAPTER 2: LITERATURE REVIEW

2.0 Introduction

This chapter discusses the underlying theories that support this study, reviews the literature related to the dependent variable (AI Dependency) and the six independent variables (Academic Self-Efficacy, Academic Stress, Performance Expectancy, Academic Workload, Time Pressure, and Social Influence), presents the proposed conceptual framework, and develops the research hypotheses.

2.1 Underlying Theory

2.1.1 Unified Theory of Acceptance and Use of Technology (UTAUT)

The Unified Theory of Acceptance and Use of Technology (UTAUT) was originally developed by Venkatesh et al. (2003). UTAUT was developed by synthesising key constructs from eight established technology acceptance models. UTAUT provides a broad framework for understanding individuals' acceptance and use of new technologies by emphasising four core constructs, which are performance expectancy, effort expectancy, social influence, and facilitating conditions (Xue et al., 2024). While UTAUT primarily focuses on behavioural intention and usage behaviour, its core constructions are highly effective in explaining the cognitive and social mechanisms that drive students to rely heavily on GenAI in their academic lives. This study uses UTAUT to investigate how students' performance views, social dynamics, and academic pressures combine to promote AI Dependency (AID) (Baharin et al., 2025).

Performance Expectancy (PE) is a fundamental construct of UTAUT. It refers to the degree to which a student believes that utilising AI will help them attain gains in their academic performance, such as improved assignment quality, faster task completion, and higher grades. In the UTAUT model, individuals who perceive a system as providing clear performance benefits are more likely to adopt it (Sumandya, 2025; Nikolic, 2024). In this study, PE captures the student's belief that GenAI is an essential asset for academic success. Students are more likely to include GenAI into their study habits when they believe it is essential to reaching their intended academic goals. Over time, students who consistently rely on AI to achieve performance objectives may go from functional usage to a condition of dependency, believing that they are unable to succeed academically without AI’s assistance (Bouteraa, 2024).

Social Influence (SI) in UTAUT reflects the extent to which a student perceives those important others. For instance, classmates, peers, or instructors believe they should use AI (Ke et al., 2025). According to the theory, this normative pressure is a significant determinant of usage. In the context of academic settings, if GenAI becomes a standard tool within a student’s peer group or if it is implicitly encouraged by the academic environment, the student feels a strong social pressure to conform. This social influence creates a situation where using AI becomes a normalised behaviour rather than a purely personal choice. As students align their habits with the academic community’s norms, this social pressure reinforces continuous AI use, thereby increasing the level of dependency on the technology to maintain social or academic standing within their cohort (Korchak, 2025).

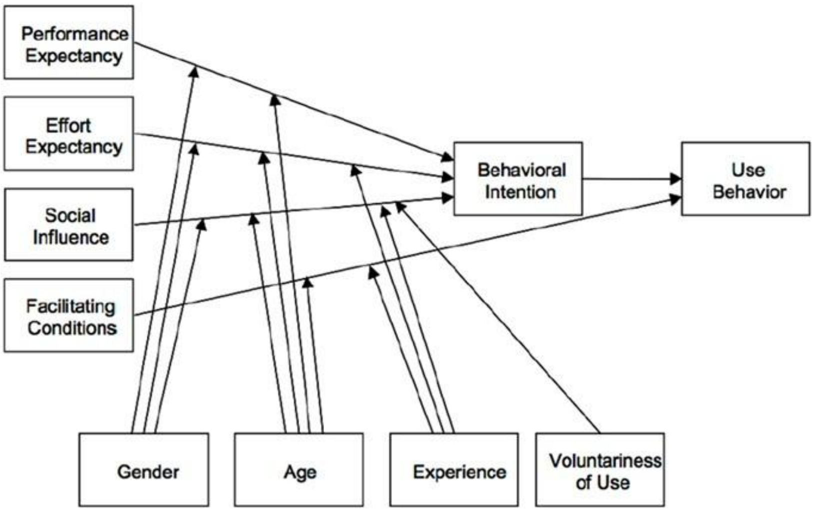
Academic Workload (AW) refers to the volume, intensity, and complexity of academic tasks students are required to complete. While AW is not an original construct of the core UTAUT model, it is introduced here as an external antecedent that substantially affects the UTAUT determinants. High academic workload acts as a situational catalyst that elevates the perceived importance of AI (Schei et al., 2024). When a student is overwhelmed by a heavy workload, the perceived performance expectancy (PE) of AI increases significantly because the tool becomes a necessary rather than optional solution for managing the volume of work (Grassini, 2024). Consequently, students under heavy academic pressure are more likely to view AI as a critical mechanism for maintaining productivity, which drives persistent and intensive usage that leads to dependency (Casimiro, 2024).

Time Pressure (TP) describes the urgent and constrained time frame within which students must complete their academic activities. Similar to academic workload, TP is an external factor that influences the UTAUT framework. Under conditions of high time pressure, students are more sensitive to the efficiency benefits offered by AI (Abbas et al., 2024). The theory suggests that when users face significant pressure to perform, their reliance on the most efficient tool increases. Therefore, TP heightens the influence of PE within the UTAUT framework. Students who are constrained by deadlines are more likely to turn to AI to shortcut the research or drafting process. This repetitive cycle of using AI to "solve" time constraints builds a dependency where the AI becomes the student's primary mechanism for survival in a high-pressure academic environment (Wang et al., 2025).

In conclusion, the UTAUT model offers an effective theoretical framework for examining the underlying reasons of AI dependency. PE functions as the cognitive driver that reflects the belief in the tool’s functional value. While SI acts as the social driver that reflects the pressure to conform to academic norms. AW and TP perform as critical external antecedents that heighten the perceived importance of AI, which effectively forces students to rely on these tools to manage their academic responsibilities. These constructs also explain how a combination of individual beliefs, social pressures, and situational demands interacts to shape students' dependency on GenAI tools in an academic context.

Figure 1

Theoretical Model of UTAUT2



Source: Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view1. *MIS quarterly*, *27*(3), 425-478.

2.1.2 Social Cognitive Theory (SCT)

Social Cognitive Theory (SCT) is one of the most important frameworks for describing human learning and behaviour, originally developed by Albert Bandura (1986). The theory explains that behaviour, environmental forces, and personal characteristics interact dynamically to produce individual behaviours through a three-dimensional reciprocal causation process. Moreover, perseverance, resilience, and decision-making are significantly influenced by the concept of self-efficacy, which is defined as a person's belief in their capacity to succeed in activities (Labrague, 2024).

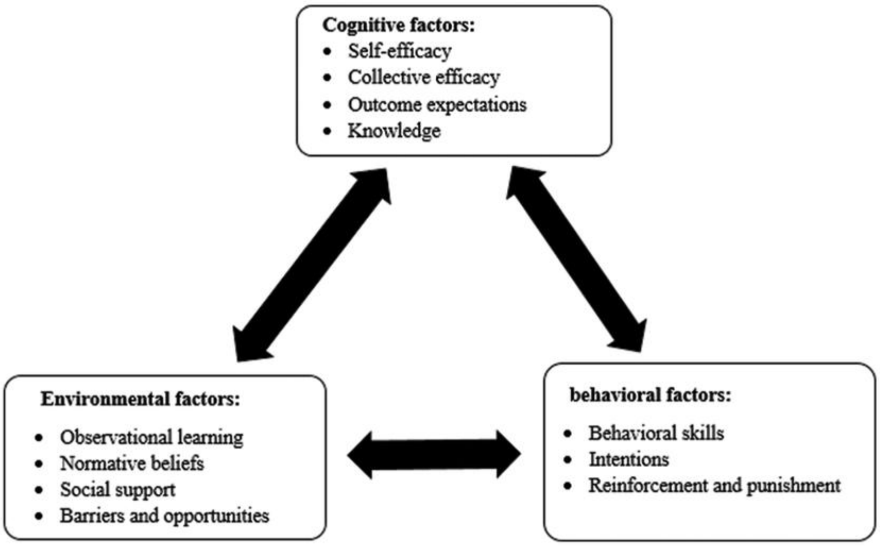
Academic achievement, learning strategies, and coping with challenges have all been continuously associated with academic self-efficacy in higher educational institutions. While students with low self-efficacy frequently resort to avoidance strategies, certain students with high self-efficacy are more inclined to actively solve problems and learn on their own (Deng & Liu, 2025; Laitinen et al., 2024). When applied to the usage of GenAI tools, SCT suggests that students who doubt their capacity to complete assignments or exams on their own may increasingly outsource these tasks to AI systems. This compensatory behaviour reinforces dependency, especially when AI provides immediate solutions without requiring cognitive effort (Bhati & Sethy, 2022).

Moreover, SCT emphasises the role of environmental stressors in influencing behaviour. Academic stress, particularly in contexts of high competition and workload, can push students toward maladaptive coping mechanisms. Students often prioritise short-term relief over long-term skill development under stress, which can manifest in the excessive use of AI for assignments (Eshet & Margaliot, 2022).

In this study, SCT provides the theoretical justification for selecting ASE and AS as independent variables. Low confidence in academic ability and heightened stress levels are hypothesised to increase students' reliance on AI, fostering dependency and reducing authentic learning. Thus, SCT not only captures the psychological underpinnings of AI misuse but also explains the mechanisms of dependency formation.

Figure 2

Constructs of Social Cognitive Theory



Source: Rad, R. E., Hosseini, Z., Mohseni, S., Mohammadi, M., Nikparvar, M., & Aghamolaei, T. (2023). Design, implementation and evaluation of an intervention based on a social cognitive theory of physical activity and nutritional behaviours in middle-aged people at the risk of coronary artery disease in Bandar Abbas: A study protocol. *Journal of Education and Health Promotion*, *12*(1), 401.

2.2 Review of the Literature

2.2.1 Dependent Variable – AI Dependency

AID is characterised by an over-reliance on artificial intelligence technology and applications that cover a variety of aspects of existence, such as social connections, daily responsibilities, and academic activities (Zhang et al., 2024). This dependence is typified by a psychological dependence on AI-assisted tools as the main tool for solving problems and making decisions, in addition to consistent utilisation of these tools. (Acosta-Enriquez et al, 2025). While dependency can sometimes be viewed neutrally as consistent use of a tool, this study emphasises its negative dimension. In particular, the research is concerned with situations where overreliance on generative artificial intelligence begins to weaken students' critical thinking and meaningful engagement in academic activities. (Uppal & Hajian, 2025).

Scholars have expressed growing concern to the students who develop excessively reliant on GenAI tools risk diminishing their cognitive engagement and creativity. As Bukhari et al. (2025) observed, over relying on GenAI for academic work might decline the opportunities for independent learning and weaken abilities in thinking critically. This risk is particularly relevant in higher educational institutions, where students are expected to cultivate analytical competencies and finding solution abilities important for their professional and individual development. When AI becomes a substitute rather than a supplement to learning, the long-term consequences may include academic underperformance and an erosion of self-directed learning capacity (Deckker & Sumanasekara, 2025).

Within the setting of this investigation, AID serves as the dependent variable (DV) because it represents the behavioural outcome influenced by multiple academic and social factors. By examining the antecedents of AID, such as ASE, AS, PE, AW, TP, and SI, this study seeks to uncover the reasons causing students' reliance on GenAI. Achieving a balance between using GenAI as a helpful tool and avoiding the drawbacks of over-reliance within learning settings requires an understanding of this connection.

2.2.2 Independent Variable 1 – Academic Self-Efficacy

Self-efficacy refers to a person's confidence in their capacity to succeed or perform well at a certain task. But it changes according to the environment or work (Schunk & DiBenedetto, 2021). It is a concept that comes from social cognitive theory (Bandura, 1986). Academic self-efficacy (ASE) is the belief in one's own ability to succeed academically (Parmaksiz, 2022). People who have strong views on their own academic effectiveness are very confident in their ability to organise, manage, and complete educational tasks. They are more eager to learn, work more, and are more determined to succeed than people who have poor ASE (Al-Abyadh & Abdel Azeem, 2022).

Lack of confidence in one's academic skills increases the possibility that a student may feel irritated and struggle to complete homework. To make up for their weaknesses in these circumstances, individuals could seek outside help, such as GenAI tools. (Tossell et al., 2024). By using GenAI tools, students may ask enquiries and get immediate, timely responses, therefore improving their educational achievement in a short time (Alshater, 2022; Rahman & Watanobe, 2023). Instead of resolving issues on their own, students can rely heavily on GenAI for temporary solutions as a result. Students with poor ASE are more likely to over-reliance to GenAI tools over time. (Zhang et al., 2024).

2.2.3 Independent Variable 2 – Academic Stress

Academic stress (AS) is a mental burden brought on by ongoing pressure to meet academic goals. It can lead to behavioural and psychological problems in students. This type of stress is frequently linked to negative emotional states including exhaustion, frustration, and anxiety, which can affect students' academic performance and cognitive abilities (Gao, 2023). Previous research has shown that AS and ASE are negatively correlated, meaning that a decline in ASE causes AS to rise (Zhang et al., 2024).

When faced with stressful circumstances, people are driven to discover coping mechanisms for their problems. On the other hand, ineffective ways to cope may increase a person's likelihood of engaging in additive or inappropriate behaviours. By providing students with an immediate and easy way to obtain educational materials and solutions, GenAI helps students meet their urgent academic obligations and reduce academic stress. (Rani et al., 2023; Zhu et al., 2023). Furthermore, research has showed that GenAI tools like chatbots can help users with psychological issues, hence enhancing their mental well-being. For instance, Meng and Dai (2021) proposed that conversing with chatbots might reduce stress and better mood. But academically stressed-out people may become more attached to GenAI tools as a result of this personalised pleasure, turning to it for emotional and intellectual assistance (Rani et al., 2023). Ultimately, people are more vulnerable to being reliant on GenAI tools.

2.2.4 Independent Variable 3 – Performance Expectancy

Performance expectation (PE) is the level at which people believe that using certain technology would improve their ability to accomplish outcomes (Zhang et al., 2024). PE in the context of GenAI refers to students' perceptions that GenAI tools can improve the quality, accuracy, and effectiveness of their academic work (Alshamy, 2025). People who lacked coping strategies to deal with various stresses felt less in control of their life, which made them act in ways that were inappropriate and risky, such as employing GenAI tools (Rehman et al., 2024). Consequently, the study called this the external pressure impacting students' academic behaviours, or performance expectations.

By using GenAI tools, they felt more in control and were less vulnerable to the negative impacts of stress and other physiological consequences. As a result, students were more inclined to use GenAI tools more often to achieve performance standards set by others (Altememy et al., 2023). Additionally, students' attention may progressively move from learning processes to performance outcomes if they consistently rely on GenAI to attain desired academic goals. This would foster surface-level engagement rather than deep learning. Over time, this behaviour might lead to a growth of AI dependency, in which students view GenAI not just as a useful tool but also as a required component for academic achievement (Guo et al., 2025).

2.2.5 Independent Variable 4 – Academic Workload

Academic workload (AW) is defined as the quantity and number of assignments, duties, and activities that students are required to do (Smith, 2021), and handling these tasks and duties is frequently a demanding situation. As a result, it is frequently linked to unpleasant feelings like tension, anxiety, or overload (Jaaskelainen et al., 2022). Students that experience a lot of tension to succeed and fulfil expectations might turn to harmful ways to deal with it, such as an excessive reliance on technology, because of the incredible stress and anxiety that this academic overload can cause (Onyinyechukwu et al., 2024).

As their academic workload rises, students are becoming more inclined to utilise GenAI tools in their everyday tasks. People use it more because it makes things easier, helps them manage their time better, and helps them achieve better in school (Sok & Heng, 2023). Exam periods and tough educational assignments like "hell weeks" saw a rise in technological usage (Hasebrook et al., 2023). GenAI tools are frequently helpful for students who have a lot on their minds in reducing stress and maintaining confidence in their academic skills. However, excessive usage of technology might result in impulsive use and reliance on GenAI tools. It has been discovered that students who have a lot of assignments utilise GenAI writing helpers as their primary tool for completing assignments instead of using them as an addition. Uncontrolled use might result in ineffective shortcuts that are abused and misused (Rasul, 2023). This uncontrolled usage can result in challenges in maintaining scholarly integrity and thinking critically (Krupp et al., 2024; Carino et al., 2024).

2.2.6 Independent Variable 5 – Time Pressure

Time pressure (TP) refers to students' perceived shortage of time when completing academic tasks, which creates a sense of urgency and stress. In higher education, TP commonly arises from tight deadlines, overlapping assignments, and the necessity of striking a balance between personal obligations and academic work (Carino et al., 2024).

TP significantly affects students' performance and their effectiveness. It can slow down motor activities and typically increase speed while decreasing precision in sensory and cognitive abilities. TP affects cognition after brain activation has started, which affects attentional concentration in basic responding and decision tasks. Furthermore, an important measure of satisfaction among users in searching for information activities is perceived time constraint. Furthermore, university students who experience more time pressure may experience greater rates of burnout and reduced productivity because of health problems (Gusy et al., 2021).

In the end, TP is the subjective belief that one does not have enough time to do activities, which frequently results in stress, a sense of helplessness, and exhaustion (Wu et al., 2022). It can impose faster resolutions and limit decision-making techniques. Since TP affects how people use and rely on these technologies, it is essential to fully understand their implications to optimise tool utilisation. Strategies to optimise the advantages of GenAI tools in academic and professional settings may be created by addressing the negative effects of time pressure, such as anxiety and exhaustion (Gusy et al., 2021).

2.2.7 Independent Variable 6 – Social Influence

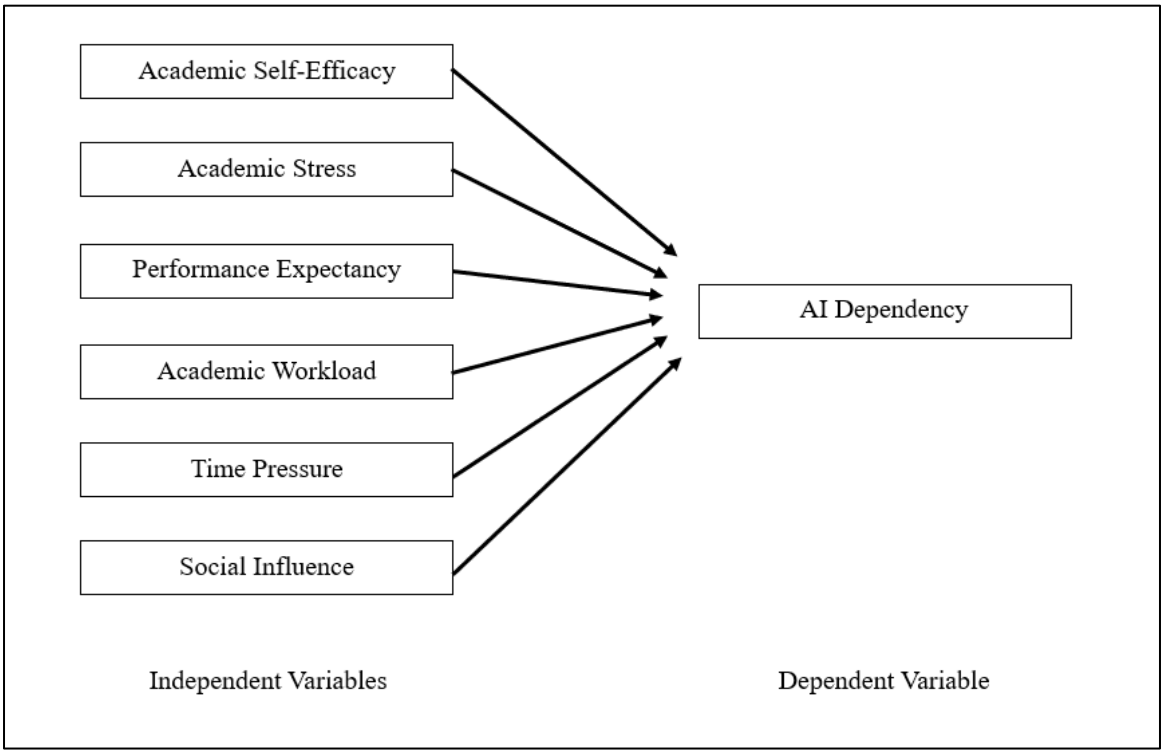
Social influence (SI) is how someone feels that important people, including friends, family, or coworkers, consider that they should utilise a certain technology (Joa & Magsamen-Conrad, 2022). According to earlier research on GenAI tools, SI may have a variety of effects on a user's willingness to utilise the tools. For instance, a positive social effect can lower risk perceptions and adoption hurdles while raising the user's opinion of the value and use of GenAI tools. Conversely, unfavourable social impact can strengthen an individual's unwillingness to modify and reflect uncertainty on the reliability and effectiveness of technology services. (Terblanche & Kidd, 2022).

There are many different sources of SI, including friends, family, coworkers, specialists, influencers, and internet comments. Positive social impact can lower perceived dangers and adoption obstacles, boost trust among users in their potential to utilise the technology efficiently, and improve the user's view of the utility and usability of GenAI tools. However, undesirable social effects might reinforce a user's resistance to change and create doubts about the ethical behaviour, precision, and reliability of GenAI tools. There are also concerns regarding the possible abuse of GenAI tools, such as the dissemination of false information, biased material, or detrimental suggestions, which might potentially give rise to negative social impact. The fact that GenAI tools were widely accepted and used more often worldwide right after their official introduction suggests that social influence has a beneficial impact on how they are adopted (Menon & Shilpa, 2023).

2.3 Proposed Conceptual Framework

Figure 3

Conceptual Framework Model



Source: Developed for the research

In this study, six independent variables are examined: ASE, AS, PE, AW, TP, and SI. The selection of these variables is grounded in established theories, where ASE and AS are derived from Social Cognitive Theory (SCT), while PE, AW, TP, and SI are informed by the Unified Theory of Acceptance and Use of Technology (UTAUT). Additionally, SI is incorporated to provide further insights into how peer expectations and academic environments contribute to students' reliance on GenAI in Malaysia.

The conceptual framework, presented in Figure 3, integrates these six independent variables to examine their collective and individual effects on the dependent variable, AID. This framework highlights the dynamic connection between personal, academic, and social factors that shape students' reliance on GenAI tools. It is hypothesised that these factors have an important and positive influence on students' AID. In other words, as students experience higher levels of stress, workload, and time pressure, or as they perceive stronger performance benefits and social endorsement, their dependency on GenAI is likely to increase. By synthesising these factors, the framework offers a structured perspective for understanding the behavioural patterns associated with GenAI usage in higher education.

2.4 Hypothesis Development

2.4.1 The relationship between academic self-efficacy and AI dependency

Numerous studies have shown how ASE directly affects university reliance of students on GenAI. Zhang et al. (2024) found that ASE influences GenAI reliance through the coordination of academic anxiety and academic achievement expectation. The results of Shen and Cui (2024), who demonstrate how GenAI literacy is mediated by the satisfaction of psychological requirements, further support this link. The student self-efficacy in university is a significant determinant of academic achievement through engagement with education (Meng & Zhang, 2023). Greco et al. (2022) established a scale that measures university students' beliefs regarding self-efficacy in academic project management.

Results in university are predicted by self-efficacy perceptions. According to Cui et al. (2023), self-efficacy in autonomous education is influenced by the academic environment. The usage of GenAI tools for educational organisations increases ethical concerns (Williams, 2023). The extent to which software development involvement is impacted by GenAI programming self-efficacy was examined. Jia & Tu (2024) have presented an organisational framework that takes self-efficacy and GenAI skills into account. Chou et al. (2022) have identified aspects that affect the efficacy of GenAI-based learning. The association between academic stress and self-efficacy, which subsequently affects GenAI reliance.

H1: There is a significant relationship between academic self-efficacy and AI dependency using GenAI among undergraduates in a Malaysian private university.

2.4.2 The relationship between academic stress and AI dependency

AS is defined as pressure produced by academic situations (Hakim, Fajri, & Faizah, 2022). Students claim that academic expectations, such as ongoing study, paper writing, preparing for exams, and boring lecturers, are the most common daily problems. (Yang, Chen, & Chen, 2021). Another important social-cognitive element that leads to improper technological usage. is AS. GenAI tools help students satisfy their immediate academic demands and reduce academic stress by providing them with a fast and easy approach to get scholarly solutions (Zhu et al., 2023). Students eventually become more susceptible to reliance on GenAI. Students who are under higher levels of AS are more likely to rely on GenAI to fulfil their academic requirements, according to the correlations found between educational stress and AID (Tamrin, 2024).

H2: There is a significant relationship between academic stress and AI dependency using GenAI among undergraduates in a Malaysian private university.

2.4.3 The relationship between performance expectancy and AI dependency

One of the most important elements affecting the adoption and application of GenAI tools in higher educational institutions is PE. According to research based on the UTAUT, PE has a significant influence on the intention of behaviour, which eventually determines how university students utilise GenAI tools. Further investigation has shown the significant influence of GenAI tools on students' educational performance, proving a clear link between the attainment of high levels of achievement and GenAI capabilities in university institutions (Altememy et al., 2023).

When it comes to the utilisation of GenAI tools, PE has also been favourably associated with student contentment and academic accomplishment. However, it is important to consider the disadvantages of using GenAI, including the possibility of reliance and its impact on thinking critically when students have high dependency on GenAI to meet high performance expectations (Zhang et al., 2024).

H3: There is a significant relationship between performance expectancy and AI dependency using GenAI among undergraduates in a Malaysian private university.

2.4.4 The relationship between academic workload and AI dependency

A student's workload is the total amount of assignments, obligations, and activities they must finish in a certain time frame, often a semester. The amount and complexity of tasks or projects are included in the workload. Students experience excessive amounts of stress when they are overloaded. (Yang et al., 2021).

According to research, stressed-out students are more likely to complete their tasks using unethical tactics rather than their own abilities and expertise. Some students resort to unethical learning behaviours, such as fraud and dishonesty due to an overwhelming workload. There was a considerable positive correlation between university students' heavy workload and stress related to studies (Koudela-Hamila et al., 2022). People who had a lot of work were better inclined to accept and utilise GenAI tools (Hasebrook et al., 2023). Students constantly look for ways to deal with this challenging situation when they are assigned a large task. To cope with these complicated circumstances, individuals consequently resort to easy fixes or artificial intelligence solutions, which may lead to high AID (Abbas et al., 2024).

H4: There is a significant relationship between academic workload and AI dependency using GenAI among undergraduates in a Malaysian private university.

2.4.5 The relationship between time pressure and AI dependency

TP is defined as the feeling that a due date comes around without warning. When people are pressed for time, they implement basic strategies to do jobs. Students facing an extensive amount of time strain could feel that they don't have enough time to do their homework, and they might turn to GenAI tools. When facing TP to finish their academic assignments, students may also use GenAI tools to cheat and plagiarise. In the same way, students under time constraints tend to use a surface-based learning strategy, which suggests that they could take shortcuts like using GenAI tools to do assignments on time (Abbas et al., 2024). Zhang (2023) showed that GenAI tools greatly increase productivity in work environments by decreasing job completion times and enhancing output quality, even for those with less competence. Over-reliance on GenAI may be impacted by a variety of factors, including work type, time constraints, and personal characteristics (Zhai et al., 2023).

H5: There is a significant relationship between time pressure and AI dependency using GenAI among undergraduates in a Malaysian private university.

2.4.6 The relationship between social influence and AI dependency

SI is the acceptance and application of artificial intelligence tools in academics that strongly influence AID. Research has shown that behavioural intent and the real usage of GenAI tools in higher educational institutions are highly influenced by social influence besides to other aspects like performance expectancy (Al-Mamary, 2024). Studies have shown that peer group influence has a beneficial effect on the intention to employ AID procedures. Furthermore, media coverage of subjects associated with AI material and interpersonal interactions about AI shifts perceptions of informative and imperative standards governing AI usage (Li et al., 2024). Peer networks are also crucial in promoting the adoption of the use of GenAI tools among educational institutions.

There may be a comparable impact on higher education academics, as it has been demonstrated that perceived organisational support favourably influences students' decision to utilise GenAI tools for their educational coursework. To implement AI into academic institutions, it is essential to consider various obstacles and ethical issues (Acosta-Enriquez et al, 2025).

H6: There is a significant relationship between social influence and AI dependency using GenAI among undergraduates in a Malaysian private university.

2.5 Chapter Summary

This chapter has covered the underlying theories, review of literature for the dependent variable (AID) and the independent variables (ASE, AS, PE, AW, TP, and SI). The conceptual framework and hypothesis development have also been discussed. The next chapter will outline the research methodology used in this study.

CHAPTER 3: METHODOLOGY

3.0 Introduction

This chapter outlines the research methodology used in this study. It describes the research design, data collection methods, sampling design, research instrument, construct measurement, data processing procedures, and data analysis techniques.

3.1 Research Design

Research design refers to the overall strategy and framework that guides the collection and analysis of data in order to answer the research questions and test hypotheses (Creswell & Creswell, 2023).

This study employed a quantitative research design with a causal approach. The quantitative method was chosen because the research aims to examine the relationships and causal effects between six independent variables (ASE, AS, PE, AW, TP, and SI) and the dependent variable (AID). Quantitative research allows for the collection of numerical data from a relatively large sample, as it enables statistical analysis to test hypotheses and generalise findings to the target population (Creswell & Creswell, 2017; Sekaran & Bougie, 2016).

A cross-sectional approach was utilised, whereby all data were collected at a single point in time through an online survey. This design is particularly suitable, because it is time-efficient and cost-effective while still allowing researchers to identify significant relationships between variables (Keedle et al., 2023).

The quantitative approach was preferred over a qualitative design because the study seeks to measure the strength and significance of relationships between variables rather than exploring in-depth personal experiences or meanings (Lim, 2024). Qualitative methods, while useful for gaining rich insights, would not enable the statistical testing of hypotheses or the quantification of how strongly each factor influences AI Dependency. Therefore, a quantitative causal design best aligns with the research objectives and allows for objective, measurable, and replicable results (Saunders et al., 2019).

3.2 Data Collection Methods

Data collection methods refer to the techniques used to gather information needed to address the research objectives and questions. These methods are typically classified into primary and secondary data (Taherdoost, 2021). This study utilised only primary data.

3.2.1 Primary Data

Primary data are original data collected firsthand by the researcher specifically for the purpose of the current study (Bello, 2023). In this research, primary data were collected through a self-administered online questionnaire distributed via Google Forms. This method enabled efficient data gathering from respondents across different campuses while ensuring anonymity and voluntary participation.

3.3 Sampling Design

Sampling design refers to the process of selecting a subset of individuals from the target population to participate in the study (Mweshi & Sakyi, 2020).

3.3.1 Target Population

The target population refers to the entire group about which the researcher wishes to make inferences (Willie, 2024). This study targeted approximately 20,000 full-time undergraduate students enrolled at Universiti Tunku Abdul Rahman (UTAR).

Universiti Tunku Abdul Rahman (UTAR) was selected as the research site because it is one of the largest private universities in Malaysia, with a steady intake of approximately 20,000 full-time undergraduate students across two main campuses (Universiti Tunku Abdul Rahman, 2025). The university offers a wide range of academic programmes across 11 faculties, encompassing diverse disciplines such as business, engineering, social sciences, creative industries, and information technology (Universiti Tunku Abdul Rahman, 2025). This diversity allows the sample to better represent Malaysian private university undergraduates. Furthermore, UTAR is consistently ranked among the top private universities in Malaysia, holding a position of #791–800 in the QS World University Rankings 2026 and #109 in the QS Asia University Rankings 2026 (EduAdvisor, 2026). In addition, UTAR has been awarded the prestigious 5 Plus Stars Outstanding Award under the QS Stars Rating system, which is the highest distinction granted by QS (Universiti Tunku Abdul Rahman, 2026). These characteristics make UTAR an appropriate and representative setting for examining GenAI dependency among Malaysian private university students.

The undergraduate faculties available in UTAR are shown in Table 1.

Table 1

List of UTAR Undergraduate Faculties

Universiti Tunku Abdul Rahman (UTAR)
Faculty of Accountancy and Management (FAM)
Faculty of Arts and Social Science (FAS)
Faculty of Creative Industries (FCI)
Faculty of Education (FEd)
Faculty of Engineering and Green Technology (FEGT)
Faculty of Information and Communication Technology (FICT)
Faculty of Science (FSc)
Faculty of Chinese Studies (FCS)
Lee Kong Chian Faculty of Engineering and Science (LKC FES)
M. Kandiah Faculty of Medicine and Health Sciences (MK FMHS)
Teh Hong Piow Faculty of Business and Finance (THP FBF)

Source: Universiti Tunku Abdul Rahman. (n.d.). Undergraduate Programmes. https://study.utar.edu.my/ug-programme-faculty.php

3.3.2 Sampling Frame and Sampling Location

A sampling frame is commonly defined as a complete list of the population from which the sample is drawn (Hitzig, 2004). In this study, no formal sampling frame was available due to privacy and data protection constraints. Instead, the undergraduate student body of UTAR was considered as the sampling frame under the Personal Data Protection Act (PDPA). UTAR is registered with the Malaysian Qualifications Agency (MQA) and holds selfaccreditation status, which assures quality practices in national higher education (Universiti Tunku Abdul Rahman, 2025).

The sampling locations are the Kampar Campus in Perak and the Sungai Long Campus in Selangor of UTAR.

3.3.3 Sampling Element

The sampling element is the individual unit from which data are collected (Turner, 2020). In this study, the sampling element was individual full-time undergraduate students currently pursuing their studies at UTAR.

3.3.4 Sampling Technique

Sampling technique refers to the specific method used to select respondents from the target population (Narayan et al., 2023). This study employed a combination of convenience and purposive sampling techniques. Purposive sampling was used to deliberately select respondents who met the specific criteria relevant to the research objectives, namely, full-time undergraduate students currently enrolled at UTAR who are actively engaged in academic tasks where GenAI tools are frequently utilised. This ensured that the sample consisted of information-rich cases most suitable for examining AI dependency. Convenience sampling was then applied to recruit participants who were readily accessible to the researcher through online platforms, university student groups, and campus networks across both the Kampar and Sungai Long campuses.

This combined non-probability sampling approach was selected primarily due to its practicality, time efficiency, and cost-effectiveness, which are essential considerations with limited time and resources. The purposive element allowed the researcher to target students from faculties with heavy assignment-based workloads, while the convenience element facilitated the collection of a sufficiently large sample in a short period. Although this sampling method may limit the generalisability of the findings to the entire population of Malaysian private university students, it remains appropriate and commonly used for causal studies conducted within a specific institutional context (Sekaran & Bougie, 2016; Zumitzavan, 2026).

3.3.5 Sampling Size

Sample size refers to the number of respondents planned to be included in the study (Lakens, 2022). According to the UTAR official website, the total student enrolment across both the Sungai Long and Kampar campuses is approximately 20,000 students (Universiti Tunku Abdul Rahman, 2025). Based on Krejcie and Morgan’s (1970) sample size determination table as shown in Figure 4, a population of this size requires a minimum sample of 377 respondents to achieve a 95% confidence level with a 5% margin of error.

Figure 4

Krejcie and Morgan Table

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

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

Source: Krejcie & Morgan, 1970

Source: Krejcie, R.V., & Morgan, D.W., (1970). Determining Sample Size for Research Activities. Educational and Psychological Measurement.

3.4 Research Instrument

A research instrument is the tool or device used by the researcher to collect data from the respondents (Wa-Mbaleka, 2019).

3.4.1 Questionnaire Design

The questionnaire consists of two main sections. Section A covers the demographic profile of the respondents, while Sections B to H contain the measurement items for the study variables.

A total of 36 items will be used to measure the seven constructs in this study: AI Dependency (5 items), Academic Self-Efficacy (7 items), Academic Stress (5 items), Performance Expectancy (5 items), Academic Workload (4 items), Time Pressure (4 items), and Social Influence (6 items). All items will be measured using a 5-point Likert scale, ranging from 1 (Strongly Disagree) to 5 (Strongly Agree).

The questionnaire will be distributed to full-time undergraduate students at UTAR. Given the widespread use of GenAI tools among university students in Malaysia, it was expected that the majority of respondents would have some experience using these tools for academic purposes.

3.4.2 Pilot Studies

A pilot study is a small-scale preliminary test conducted to evaluate the reliability, clarity, and feasibility of the research instrument before the main data collection (Matimbwa & Ringo, 2025).

A pilot test was conducted with 30 undergraduate students from UTAR prior to the main survey. The pilot questionnaire was distributed via Google Forms, and the collected data were analysed using IBM SPSS Statistics (Version 31). Reliability analysis was performed using Cronbach's Coefficient Alpha, as shown in Table 2, which follows the rule of thumb suggested by Gottems et al. (2018).

Table 2

The Rule of Thumb of Cronbach's Coefficient Alpha

Cronbach's Coefficient Alpha (α) Value	**Strength of Association**
Less than 0.60	Poor reliability
0.60 to 0.70	Fair reliability
0.70 to 0.80	Good reliability
0.80 to 0.95	Excellent reliability

Source: George, D., and Mallery, M. (2003). Using SPSS for Windows step by step: a simple guide and reference.

Table 3

Reliability Test Result (Pilot Study)

Variable	**Cronbach's Alpha Value**	**Number of Items**	**Reliability Level**
Dependent Variable:			
AI Dependency	0.711	5	Good
Independent Variables:			
Academic Self-Efficacy	0.891	7	Excellent
Academic Stress	0.617	5	Fair
Performance Expectancy	0.762	5	Good
Academic Workload	0.782	4	Good
Time Pressure	0.826	4	Excellent
Social Influence	0.825	6	Excellent

Source: Developed for the research

As shown in Table 3, the Cronbach's Alpha values for the constructs were as follows: AID (0.711), ASE (0.891), AS (0.617), PE (0.762), AW (0.782), TP (0.826), and SI (0.825). Most constructs showed acceptable reliability (≥

0.70), with Academic Stress being marginally acceptable (≥ 0.60). Minor adjustments to wording were made based on pilot feedback before full distribution.

3.5 Construct Measurement

Construct measurement refers to the process of operationalising abstract concepts (variables) into measurable indicators using appropriate scales (Mueller, 2004).

3.5.1 Nominal Scale

Nominal scale is the lowest level of measurement used to categorise data into mutually exclusive groups without any inherent order (Dalati, 2018). In this study, four questions in Section A are on a nominal scale: Question 1 (Gender), Question 3 (UTAR Campus), Question 4 (Faculty), and Question 6 (Main Purpose of GenAI Use).

1. Gender:

[ ] Male

[ ] Female

3.5.2 Ordinal Scale

Ordinal scale is a level of measurement that involves ranking or ordering of categories. It will be applied where appropriate for variables involving ranking or ordering (Lalla, 2017). Two demographic questions in Section A are ordinal: Question 2 (Age) and Question 5 (GenAI Usage Frequency).

2. Age:

[ ] 18 – 21

[ ] 22 – 25

[ ] 26 – 29

[ ] 30 and above

3.5.3 Interval Scale

Interval scale is a level of measurement that assumes equal intervals between values but lacks a true zero point (Yusoff, 2014). The 5-point Likert scale to be used for all construct items will be treated as an interval scale. This will allow the computation of means, standard deviations, and parametric statistical tests. In this study, all items in Sections B to H (AID, ASE, AS, PE, AW, TP, and SI) are measured using a five-point Likert scale.

1 = Strongly Disagree

2 = Disagree

3 = Neutral

4 = Agree

5 = Strongly Agree

No.	Questions	Strongly Disagree	Disagree	Neutral	Agree	Strong Agree
1.	I feel anxious when I cannot use GenAI tools for my academic tasks.	1	2	3	4	5

3.5.4 Origin of Measure of Construct

This study uses the operational definition for the key construct as shown in Table 4.

Table 4

Operational Definition of the Key Construct

Variable	**Item**	**Construct Measurement**	**Sources**
AI Dependency	5	• I feel anxious when I cannot use AI tools for my academic tasks. • I rely excessively on AI to complete my academic assignments. • I have difficulty performing academic tasks without AI support. • I feel the need to use AI with increasing frequency to maintain my academic performance. • I find it difficult to control the time I spend using AI tools.	Adopted and adapted from Acosta-Enriquez et al. (2025)

Academic Self-Efficacy	7	• I am confident in my ability to understand the most complex concepts presented in class. • I am certain I can do an excellent job on assignments and examinations. • I can master the skills being taught in my course. • I am confident in my ability to learn course material independently. • I can successfully complete all assigned tasks regardless of their difficulty. • I am capable of achieving good academic result through my own merit. • I can achieve my academic goals even when facing challenges.	Adopted and adapted from Acosta-Enriquez et al. (2025)
Academic Stress	5	• I feel overwhelmed by the amount of academic work I have. • I experience anxiety when facing academic deadlines. • I worry about not being able to meet academic expectations. • I feel pressure to maintain good academic performance. • Academic stress affects my ability to concentrate.	Adopted and adapted from Acosta-Enriquez et al. (2025)
Performance Expectancy	5	• Using AI improves my academic performance. • AI helps me complete my academic tasks more quickly. • AI increase my academic productivity. • Using AI makes my academic tasks more efficient. • AI tools help me achieve better grades.	Adopted and adapted from Acosta-Enriquez et al. (2025)

Academic Workload	4	• My academic workload (Lecture, assignments, examinations, etc.) is too heavy to control. • I feel overloaded from organizing the work my studies require. • I feel overburdened due to the lack of a clear plan for managing my studies. • The instructors give too much work to do, which makes it difficult to motivate myself to finish tasks.	Adopted and adapted from Carino et al. (2024)
Time Pressure	4	• I often struggle to allocate sufficient time to thoroughly prepare for my class projects (Lecture, assignments, examinations, etc.) due to heavy academic workload. • I find it challenging to allocate enough time for study-related tasks (reviewing lecture notes, completing assigned tasks, do tutorials) while maintaining the quality and thoroughness required. • I experience difficulty in consistently meeting submission deadlines for my assignments and projects due to overlapping academic commitments and time constraints. • I frequently feel rushed or in a hurry to complete academic tasks and projects on time, leading to a sense of urgency when meeting deadlines.	Adopted and adapted from Carino et al. (2024)

Social Influence	6	• Social media recommendations to use AI tools. • My friends and family suggest using GenAI tools. • I discuss GenAI tools with my classmates/friends. • My research colleagues think I should use GenAI tools. • My university is supportive and provides guidelines to help students use GenAI tools effectively in their research. • My academic community supports the use of GenAI tools in research.	Adopted and adapted from Acosta-Enriquez et al. (2025); Menon et al. (2023)

Source: Developed for the research

3.6 Data Processing

Data processing refers to the series of steps to be taken to prepare raw data for statistical analysis (Huang, 2022).

3.6.1 Data Checking

Data checking involves the initial verification of the completeness and consistency of the collected responses. In this study, the researcher carefully reviewed all returned questionnaires to identify any errors, incomplete answers, or inconsistencies before further processing (Hossan et al., 2025).

3.6.2 Data Editing

Data editing is the process of reviewing and correcting inaccurate, incomplete, or ambiguous responses. The researcher examined the responses and made necessary corrections to improve clarity and accuracy, thereby increasing the reliability of the subsequent analysis (Palikhe & Phuyal, 2025).

3.6.3 Data Coding

Data coding refers to the assignment of numerical values to questionnaire responses to facilitate statistical analysis (Kotronoulas et al., 2023). In this study, responses were systematically coded in SPSS. For Section A, each question's answer is coded as shown in Table 5 below.

Table 5

Coding of Question in Section A

	Question	Item	Coding
1.	Gender	Male	1
		Female	2
2.	Age	18 – 21	1
		22 – 25	2
		26 – 29	3
		30 and above	4
3.	UTAR Campus	Kampar Campus	1
		Sungai Long Campus	2

4.	Faculty	Faculty of Accountancy and Management (FAM)	1
		Faculty of Arts and Social Science (FAS)	2
		Faculty of Creative Industries (FCI)	3
		Faculty of Education (FEd)	4
		Faculty of Engineering and Green Technology (FEGT)	5
		Faculty of Information and Communication Technology (FICT)	6
		Faculty of Science (FSc)	7
		Faculty of Chinese Studies (FCS)	8
		Lee Kong Chian Faculty of Engineering and Science (LKC FES)	9
		M. Kandiah Faculty of Medicine and Health Sciences (MK FMHS)	10
		Teh Hong Piow Faculty of Business and Finance (THP FBF)	11
5.	How frequently do you use GenAI tools per week?	1 – 2 times per week	1
		3 – 5 times per week	2
		Once per day	3
		Multiple times per day	4
6.	What do you mostly use GenAI tools for?	Exam preparation (e.g., revision summaries, practice questions)	1
		Assignment guidance (e.g., structuring assignments, project planning)	2
		Daily study support (e.g. note-taking, summarisation of lecture materials)	3

	Research assistance (e.g. finding sources, explaining research concepts)	4
	Writing assistance (e.g. paraphrasing, grammar checking, improving academic writing)	5
	Idea generation or brainstorming (e.g. essay topics, project ideas, outlining arguments)	6
	Language translation (e.g. translating academic materials, multilingual explanations)	7

Source: Developed for the research

Each question's response in Sections B to H was coded using the 5-point Likert scale as follows:

- “Strongly Disagree” is coded as 1
- “Disagree” is coded as 2
- “Neutral” is coded as 3
- “Agree” is coded as 4
- “Strongly Agree” is coded as 5

3.6.4 Data Transcribing

Data transcribing involves transferring the collected data into analysis software (Olayemi et al., 2022). In this study, data collected via Google Forms were directly exported into SPSS software (Version 31) for further processing. The dataset was then saved in a secure cloud drive for backup and subsequent analysis.

3.6.5 Data Cleaning

Data cleaning is the process of detecting and correcting errors, outliers, duplicates, and missing values in the dataset. Listwise deletion was applied for cases with substantial missing data. This step is essential to ensure the quality of data before running statistical analyses (Sharifnia, 2026).

3.7 Data Analysis

Data analysis refers to the techniques and procedures used to process and interpret the collected data in order to answer the research questions and test the proposed hypotheses (Alem, 2020). In this stage, the study data were converted into clear and practical information using SPSS software.

3.7.1 Descriptive Analysis

Descriptive analysis summarises and organises the main characteristics of the dataset using measures such as frequency, percentage, mean, standard deviation, and graphical representations (pie charts and bar charts). It will be used to describe the respondents' demographic profile and the central tendencies of each construct (Cooksey, 2020).

3.7.2 Scale Measurement

Scale measurement involves assessing the quality of the measurement scales, particularly their reliability. Reliability analysis will be conducted using Cronbach's Alpha. Prior to inferential analysis, assumption tests will be performed, including normality (skewness and kurtosis), multicollinearity (Tolerance and Variance Inflation Factor), and linearity. It is to ensure the data is able to meet the requirements for multiple regression analysis.

3.7.3 Inferential Analysis

Inferential analysis enables researchers to draw conclusions about the population based on sample data and to examine relationships between variables (Lee & Kim, 2022). It consists of two main techniques as follows:

3.7.3.1 Pearson Correlation Coefficient Analysis

Pearson Product-Moment Correlation Coefficient will be used to examine the strength and direction of the bivariate relationships between the independent variables and the dependent variable (AI Dependency).

3.7.3.2 Multiple Linear Regression Analysis

Multiple Linear Regression Analysis will be employed to test the research hypotheses and determine the extent to which the six independent variables (ASE, AS, PE, AW, TP, and SI) collectively predict AI Dependency. It will also identify which independent variables are significant predictors of the dependent variable.

3.8 Chapter Summary

This chapter has detailed the research methodology to be adopted in this study, from research design through to data analysis techniques. The following chapter will present the findings obtained from the data analysis.

CHAPTER 4: DATA ANALYSIS

4.0 Introduction

This chapter presents the results of the data analysis conducted to address the research objectives and hypotheses of the study. It includes descriptive analysis of the respondents' demographic profile, reliability analysis, assumption tests, and inferential analysis.

4.1 Descriptive Analysis

This section presents the descriptive statistics of the data collected from the survey. A total of 388 valid questionnaires were collected and analysed in this study. This sample size slightly exceeded the target of 377 respondents planned in the methodology chapter.

4.1.1 Respondent Demographic Profile

4.1.1.1 Gender

Table 6

Respondent's Gender

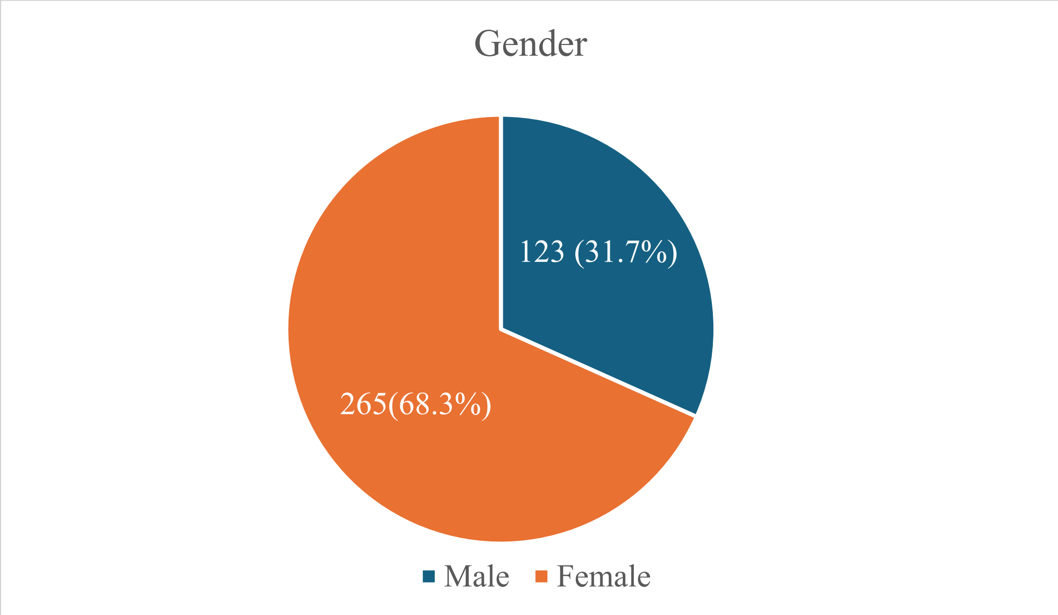
Gender	Frequency	Percentage (%)	Cumulative Frequency	Cumulative Percentage (%)
Male	123	31.7	123	31.7

Female	265	68.3	388	100.0

Source: Developed for the research

Figure 5

Statistics for Respondent's Gender



Source: Developed for the research

There is a total of 31.7% (123) of male respondents, while the female respondents consist of 68.3% (265), as shown in Table 6 and Figure 5.

4.1.1.2 Age

Table 7

Respondent's Age

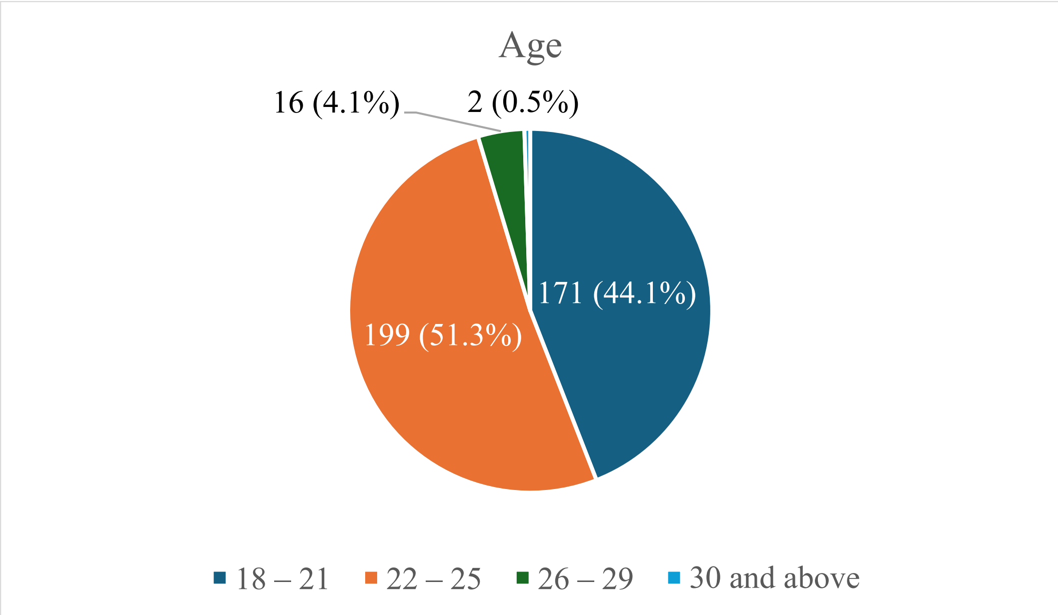
Age	Frequency	Percentage (%)	Cumulative Frequency	Cumulative Percentage (%)

18 – 21	171	44.1	171	44.1
22 – 25	199	51.3	370	95.4
26 – 29	16	4.1	386	99.5
30 and above	2	0.5	388	100.0

Source: Developed for the research

Figure 6

Statistics for Respondent's Age



Source: Developed for the research

Based on Table 7 and Figure 6, there are a total of 44.1% (171) respondents between 18 to 21. 51.4% (199) of respondents are between 22 to 25, and 4.1% (16) of respondents are between 26 to 29. The rest 0.5% (2) of respondents are 30 and above.

4.1.1.3 UTAR Campus

Table 8

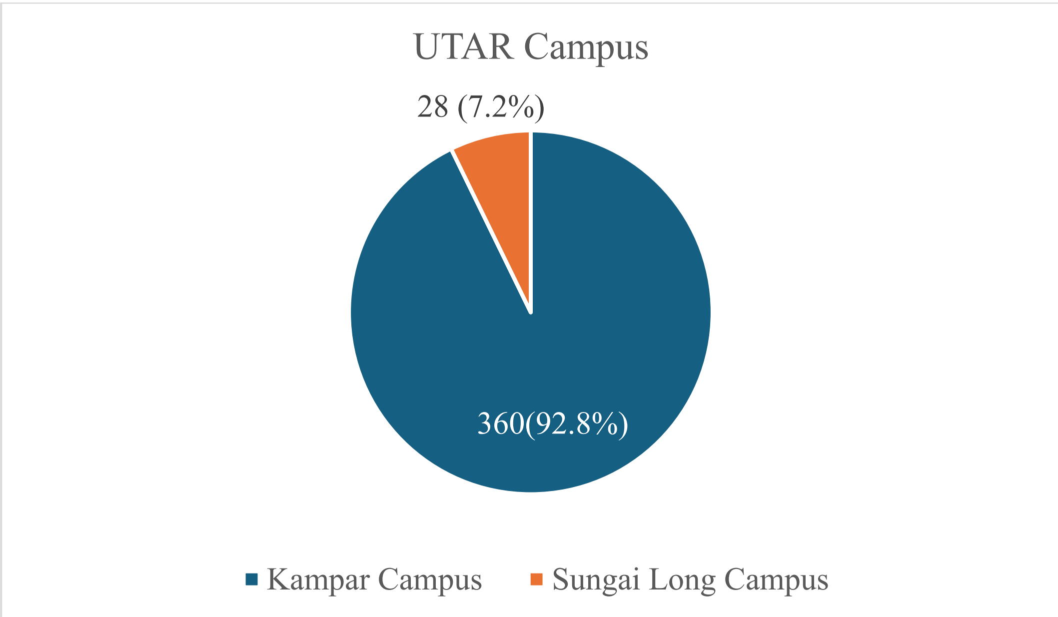
Respondent's UTAR Campus

UTAR Campus	Frequency	Percentage (%)	Cumulative Frequency	Cumulative Percentage (%)
Kampar Campus	360	92.8	360	92.8
Sungai Long Campus	28	7.2	388	100.0

Source: Developed for the research

Figure 7

Statistics for Respondent's UTAR Campus



Source: Developed for the research

There are 92.8% (360) respondents from UTAR Kampar Campus and 7.2% (28) respondents from UTAR Sungai Long Campus as shown in Table 8 and Figure 7.

4.1.1.4 Faculty

Table 9

Respondent's Faculty

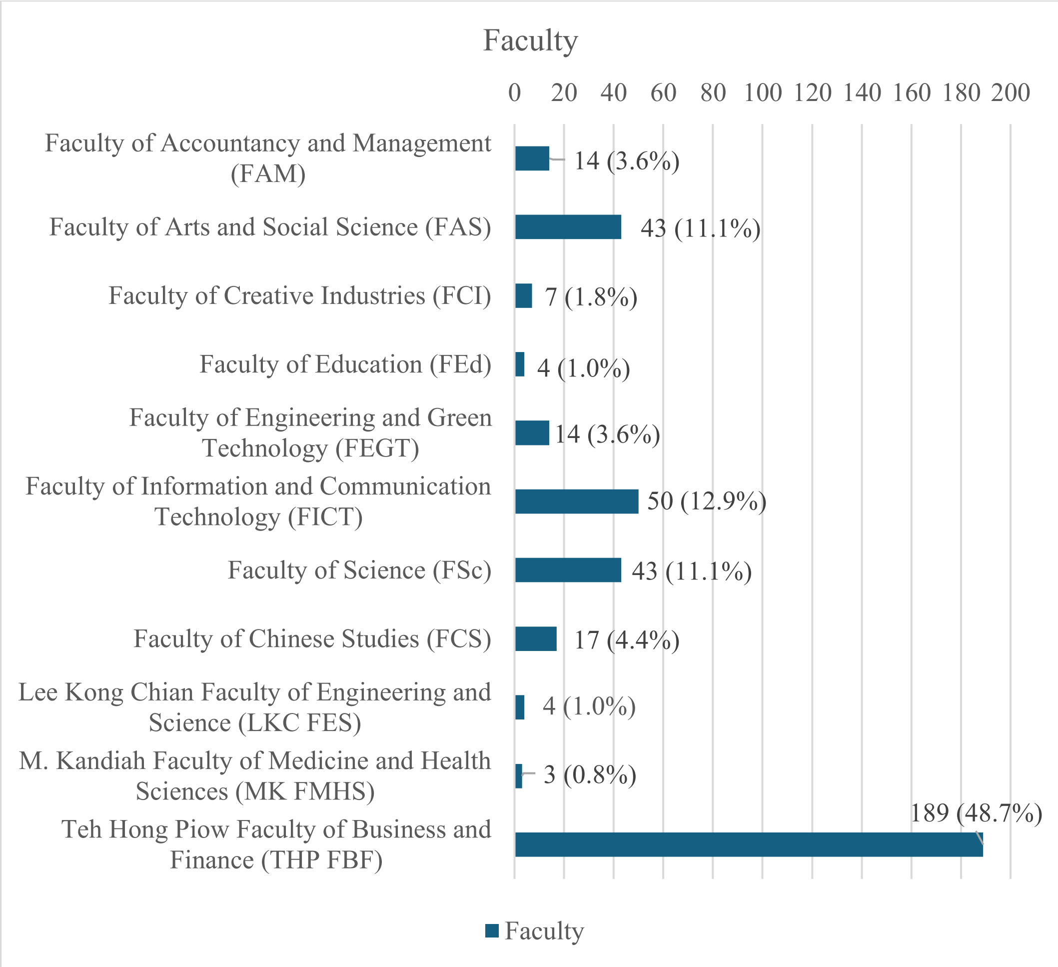
Faculty	**Frequency**	**Percentage (%)**	**Cumulative Frequency**	**Cumulative Percentage (%)**
Faculty of Accountancy and Management (FAM)	14	3.6	14	3.6
Faculty of Arts and Social Science (FAS)	43	11.1	57	11.7
Faculty of Creative Industries (FCI)	7	1.8	64	16.5
Faculty of Education (FEd)	4	1.0	68	17.5
Faculty of Engineering and Green Technology (FEGT)	14	3.6	82	21.1

Faculty of Information and Communication Technology (FICT)	50	12.9	132	34.0
Faculty of Science (FSc)	43	11.1	175	45.1
Faculty of Chinese Studies (FCS)	17	4.4	192	49.5
Lee Kong Chian Faculty of Engineering and Science (LKC FES)	4	1.0	196	50.5
M. Kandiah Faculty of Medicine and Health Sciences (MK FMHS)	3	0.8	199	51.3
Teh Hong Piow Faculty of Business and Finance (THP FBF)	189	48.7	388	100.0

Source: Developed for the research

Figure 8

Statistics for Respondent's Faculty



Source: Developed for the research

Based on Table 9 and Figure 8, for Kampar Campus, a total of 3.6% (14) respondents from Faculty of Accountancy and Management, 11.1% (43) respondents from Faculty of Arts and Social Science, 3.6% (914) respondents from Faculty of Engineering and Green Technology, 12.9% (50) respondents from Faculty of Information and Communication Technology, 11.1% (43) respondents from Faculty of Science, 48.7% (189) respondents from Teh Hong Piow Faculty of Business and Finance, 4.4% (17) respondents from Faculty of Chinese Studies, and 1.0% (4) respondents from Faculty of Education. For Sungai Long Campus, 0.8% (3) respondents from M. Kandiah Faculty of Medicine and Health Sciences, 1.0% (4)

respondents from Lee Kong Chian Faculty of Engineering and Science, and 1.8% (7) respondents from Faculty of Creative Industries.

4.1.1.5 GenAI Usage Frequency

Table 10

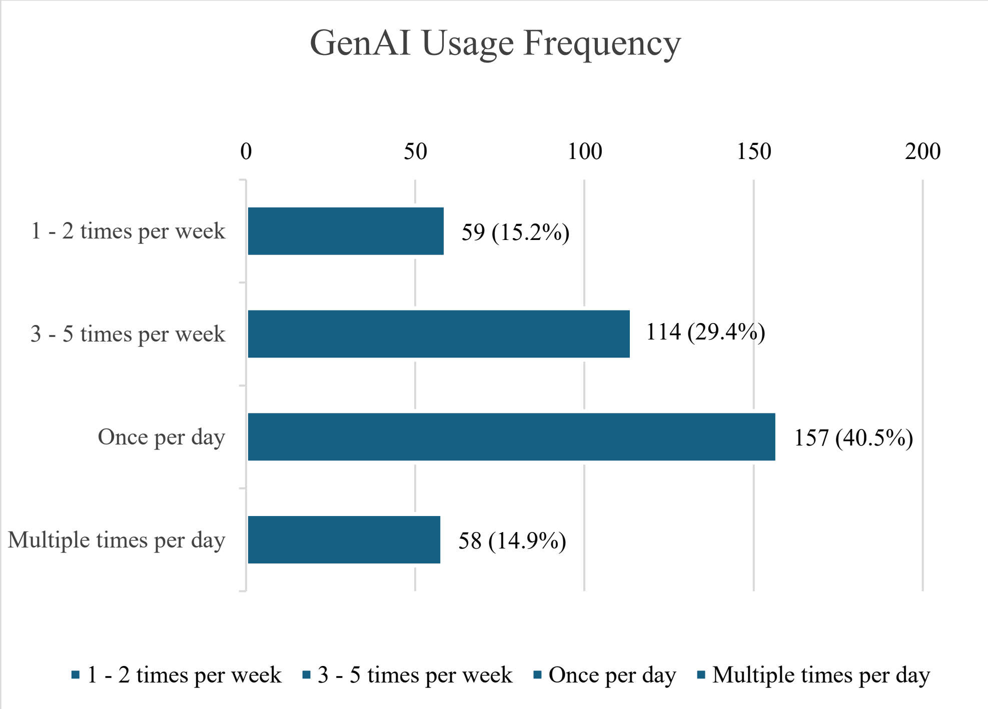
Respondent's GenAI Usage Frequency

GenAI Usage Frequency	Frequency	Percentage (%)	Cumulative Frequency	Cumulative Percentage (%)
1 - 2 times per week	59	15.2	59	15.2
3 - 5 times per week	114	29.4	173	44.6
Once per day	157	40.5	330	85.1
Multiple times per day	58	14.9	388	100.0

Source: Developed for the research

Figure 9

Statistics for Respondent's GenAI Usage Frequency



Source: Developed for the research

From a 388 set of questionnaires collected, there are 15.2% (59) respondents that use GenAI 1 -2 times per week. Besides, responses that use 3 – 5 times per week consist of 29.4% (114) respondents, while responses that use once per day consist of 40.5% (157). Responses that are used multiple times per day consist of 14.9% (58).

4.1.1.5 Main Purpose of GenAI Use

Table 11

Respondent's Main Purpose of GenAI Use

Main Purpose of GenAI Use	Frequency	Percentage (%)	Cumulative Frequency	Cumulative Percentage (%)
Exam preparation	48	12.4	48	12.4

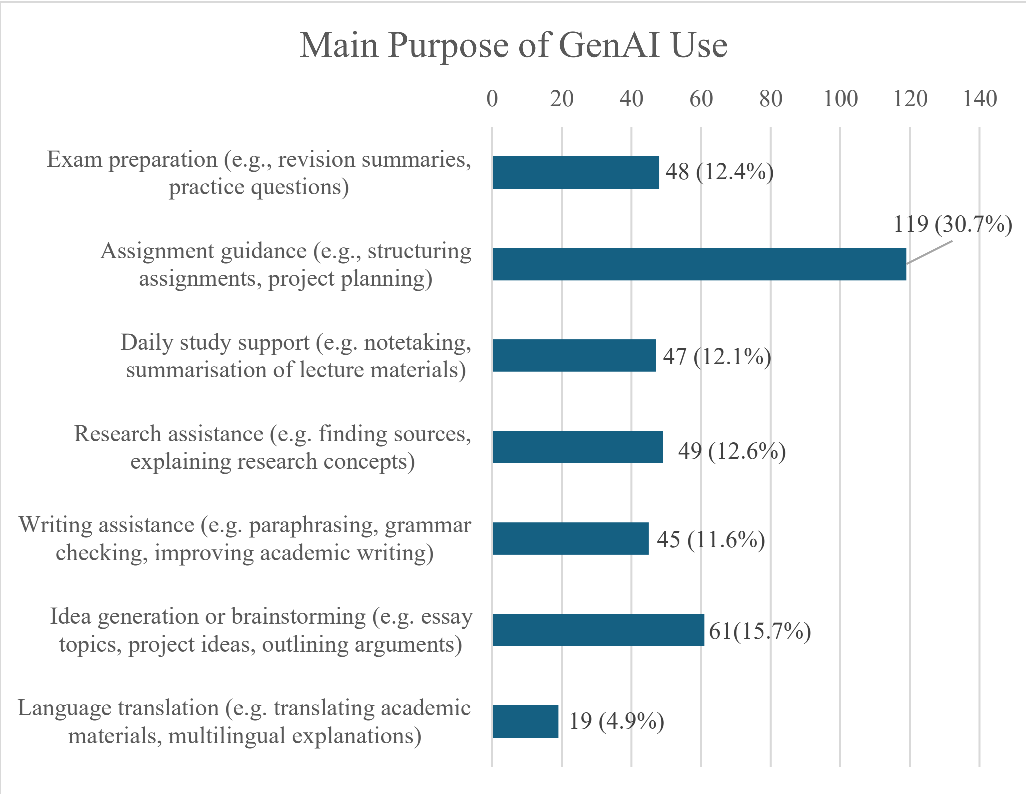
(e.g., revision summaries, practice questions)				
Assignment guidance (e.g., structuring assignments, project planning)	119	30.7	167	43.1
Daily study support (e.g. notetaking, summarisation of lecture materials)	47	12.1	214	55.2
Research assistance (e.g. finding sources, explaining research concepts)	49	12.6	263	67.8
Writing assistance (e.g. paraphrasing, grammar checking, improving academic writing)	45	11.6	308	79.4

Idea generation or brainstorming (e.g. essay topics, project ideas, outlining arguments)	61	15.7	369	95.1
Language translation (e.g. translating academic materials, multilingual explanations)	19	4.9	388	100.0

Source: Developed for the research

Figure 10

Statistics for Respondents' GenAI Usage Frequency



Source: Developed for the research

The Main Purpose of GenAI Usage represents the last category of demographic categories analysed. Based on Table 11 and Figure 10, most respondents use GenAI for assignment guidance which consist of 30.7% (119) respondents. Following by idea generation or brainstorming 15.7% (61) respondents, research assistance 12.6% (49) respondents, exam preparation 12.4% (48) respondents, daily study support 12.1% (47), and writing assistance 11.6% (45). The least GenAI usage is language translation that consists of 4.9% (19).

4.1.2 Central Tendencies Measurement of Constructs

4.1.2.1 AI Dependency

Table 12

Central Tendency Measurement for AI Dependency

Question	Statement	Mean	Standard Deviation	Mean Ranking	Standard Deviation Ranking
AID 1	I feel anxious when I cannot use GenAI tools for my academic tasks.	3.56	1.046	3	5
AID 2	I rely excessively on	3.68	1.140	2	2

	GenAI to complete my academic assignments.				
AID 3	I have difficulty performing academic tasks without GenAI support.	3.53	1.082	4	3
AID 4	I feel the need to use GenAI with increasing frequency to maintain my academic performance.	3.74	1.067	1	4
AID 5	I find it difficult to control the time I spend using GenAI tools.	3.15	1.293	5	1

Source: Generated from SPSS software (Version 31)

Table 12 illustrates that AID4 has the highest mean value of 3.74, which indicates that most respondents agreed with it. Followed by AID2 (3.68), AID1 (3.56), AID3 (3.53), and AID5 (3.15). AID5 obtained the highest standard deviation value of 1.293, followed by AID2 (1.140), AID3 (1.082), AID4 (1.067), and AID1 (1.046).

4.1.2.2 Academic Self-Efficacy

Table 13

Central Tendency Measurement for Academic Self-Efficacy

Question	Statement	Mean	Standard Deviation	Mean Ranking	Standard Deviation Ranking
ASE 1	I am confident in my ability to understand the most complex concepts presented in class.	3.33	1.087	7	2
ASE 2	I am certain I can do an excellent job on assignments and examinations.	3.56	1.071	4	3
ASE 3	I can master the skills being taught in my course.	3.43	1.033	6	4
ASE 4	I am confident in my ability to learn course	3.53	1.089	5	1

	material independently.				
ASE 5	I can successfully complete all assigned tasks regardless of their difficulty.	3.61	0.954	3	7
ASE 6	I am capable of achieving good academic result through my own merit.	3.65	0.968	2	6
ASE 7	I can achieve my academic goals even when facing challenges.	3.72	1.017	1	5

Source: Generated from SPSS software (Version 31)

Table 13 illustrates that ASE7 has the highest mean value of 3.72, which indicates that most respondents agreed with it. Followed by ASE6 (3.65), ASE5 (3.61), ASE2 (3.56), ASE4 (3.53), ASE3 (3.43), ASE1 (3.33). ASE4 obtained the highest standard deviation value of 1.089.

4.1.2.3 Academic Stress

Table 14

Central Tendency Measurement for Academic Stress

Question	Statement	Mean	Standard Deviation	Mean Ranking	Standard Deviation Ranking
AS 1	I feel overwhelmed by the amount of academic work I have.	3.72	0.966	4	5
AS 2	I experience anxiety when facing academic deadlines.	4.01	1.029	1	2
AS 3	I worry about not being able to meet academic expectations.	3.88	0.976	3	4
AS 4	I feel pressure to maintain g ood academic performance.	3.89	0.985	2	3
AS 5	Academic stress affects my ability to concentrate.	3.716	1.048	5	1

Source: Generated from SPSS software (Version 31)

Table 14 illustrates that AS2 has the highest mean value of 4.01, which indicates that most respondents agreed with it. AS5 obtained the highest standard deviation value of 1.048.

4.1.2.4 Performance Expectancy

Table 15

Central Tendency Measurement for Performance Expectancy

Question	Statement	Mean	Standard Deviation	Mean Ranking	Standard Deviation Ranking
PE 1	Using GenAI improves my academic performance.	4.01	0.834	5	4
PE 2	GenAI helps me complete my academic tasks more quickly.	4.20	0.886	1	1
PE 3	GenAI increases my academic productivity.	4.11	0.845	3	3
PE 4	Using GenAI makes my academic	4.18	0.821	2	5

	tasks more efficient.				
PE 5	GenAI tools help me achieve better grades.	4.09	0.846	4	2

Source: Generated from SPSS software (Version 31)

Table 15 illustrates that PE2 has the highest mean value of 4.20, which indicates that most respondents agreed with it. PE1 also obtained the highest standard deviation value of 0.886.

4.1.2.5 Academic Workload

Table 16

Central Tendency Measurement for Academic Workload

Question	Statement	Mean	Standard Deviation	Mean Ranking	Standard Deviation Ranking
AW 1	My academic workload (lectures, assignments, examinations, etc.) is too heavy to control.	3.63	0.997	3	4

AW 2	I feel overloaded from organising the work my studies require.	3.74	1.110	1	2
AW 3	I feel overburdened due to the lack of a clear plan for managing my studies.	3.64	1.108	2	3
AW 4	The instructors give too much work to do, which makes it difficult to motivate myself to finish tasks.	3.59	1.148	4	1

Source: Generated from SPSS software (Version 31)

Table 16 shows that AW2 has the highest mean value of 3.74, which indicates that most respondents agreed with it. AW1 obtained the highest standard deviation value of 1.148.

4.1.2.6 Time Pressure

Table 17

Central Tendency Measurement for Time Pressure

Question	Statement	Mean	Standard Deviation	Mean Ranking	Standard Deviation Ranking
TP 1	I often struggle to allocate suffic ient time to thoroughly prepare for my class projects (lectures, assignments, examinations, etc.) due to heavy academic workload.	3.65	1.036	4	4
TP 2	I find it challenging to allocate enou gh time for study-related tasks (reviewing lecture notes, completing assigned tasks, doing tutorials) while maintainin g the quality and	3.80	1.043	1	3

	thoroughness required.				
TP 3	I experience difficulty in consistently meeting submission deadlines for my assignments and projects due to overlapping academic commitments and time constraints.	3.67	1.104	3	1
TP 4	I frequently feel rushed or in a hurry to complete academic tasks and projects on time, leading to a sense of urgency when meeting deadlines.	3.77	1.062	2	2

Source: Generated from SPSS software (Version 31)

Table 17 shows that TP2 has the highest mean value of 3.80, which indicates that most respondents agreed with it. TP3 obtained the highest standard deviation value of 1.104.

4.1.2.7 Social Influence

Table 18

Central Tendency Measurement for Social Influence

Question	Statement	Mean	Standard Deviation	Mean Ranking	Standard Deviation Ranking
SI 1	Social media recommends using GenAI tools.	4.04	0.953	1	5
SI 2	My friends and family suggest using GenAI tools.	3.83	0.941	3	6
SI 3	I discuss GenAI tools with my classmates/friends.	3.84	1.004	2	2
SI 4	My research colleagues think I should use GenAI tools.	3.74	0.973	4	4
SI 5	My university is supportive and provides guidelines to help students use GenAI tools effectively in their research.	3.66	1.002	6	3
SI 6	My academic community supports the use	3.70	1.010	5	1

	of GenAI tools in research.

Source: Generated from SPSS software (Version 31)

Table 18 shows that SI1 has the highest mean value of 4.04, which indicates that most respondents agreed with it. SI6 obtained the highest standard deviation value of 1.010.

4.2 Scale Measurement

4.2.1 Reliability Test

Table 19

Cronbach's Alpha Reliability Test

Variable	Cronbach's Alpha Value	Number of Items	Reliability Level
Dependent Variable:			
AI Dependency	0.899	5	Excellent
Independent Variables:			
Academic Self-Efficacy	0.925	7	Excellent
Academic Stress	0.862	5	Excellent
Performance Expectancy	0.889	5	Excellent
Academic Workload	0.883	4	Excellent
Time Pressure	0.881	4	Excellent
Social Influence	0.843	6	Excellent

Source: Developed for the research

The reliability of the 388 sets of questionnaires has been determined using a reliability test in SPSS. Based on Table 19, the Cronbach's Alpha values for all variables ranged from 0.843 to 0.925. All variables have obtained a Cronbach's Alpha value of more than 0.80, which means that all variables have excellent reliability.

4.3 Preliminary Data Analysis

4.3.1 Multicollinearity Test

Table 20

Tolerance Value and Variance Inflation Factor (VIF)

Independent Variables	Collinearity Statistics	
	VIF	**Tolerance**
Academic Self-Efficacy	0.891	1.123
Academic Stress	0.381	2.626
Performance Expectancy	0.583	1.714
Academic Workload	0.307	3.254
Time Pressure	0.271	3.691
Social Influence	0.509	1.965

Source: Generated from SPSS software (Version 31)

The multicollinearity test was conducted to check for high correlations among the independent variables. As shown in Table 20, the Tolerance values ranged from 0.271 to 0.891 and the VIF values ranged from 1.123 to

3.691. All Tolerance values were above 0.10 and all VIF values were below 5. These results indicate that multicollinearity was not a problem in this study. Therefore, the data satisfied the multicollinearity assumption and were suitable for multiple linear regression analysis.

4.3.2 Normality Test

The normality of the data was assessed using skewness and kurtosis statistics. A distribution is considered approximately normal if the skewness value falls between -2 and +2, and the kurtosis value falls between -7 and +7.

Table 21

Result of Normality Test

Variables	Skewness	Kurtosis
Dependent Variable:		
AI Dependency	(0.676)	(0.122)
Independent Variables:		
Academic Self-Efficacy	(0.407)	(0.365)
Academic Stress	(1.048)	0.892
Performance Expectancy	(1.376)	2.875
Academic Workload	(0.709)	(0.119)
Time Pressure	(0.813)	(0.019)
Social Influence	(0.564)	0.279

Source: Generated from SPSS software (Version 31)

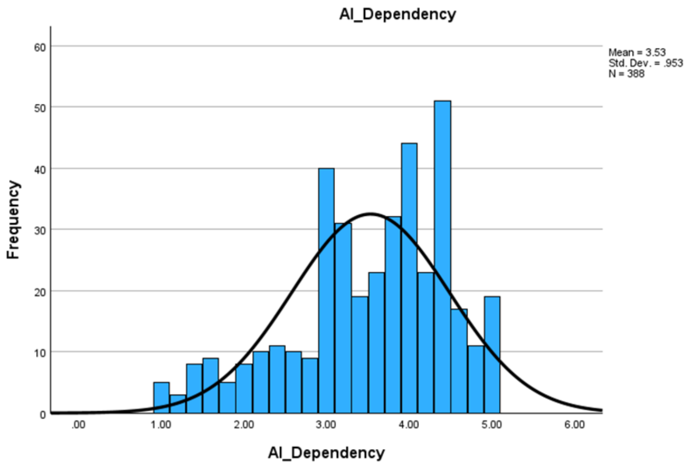
Table 21 shows that the skewness values ranged from -1.376 to -0.407, and the kurtosis values ranged from -0.365 to 2.875. All values were well within the acceptable ranges. Therefore, the data for all variables were considered approximately normally distributed, as they could satisfy the normality assumption required for multiple linear regression analysis.

4.3.2.1 Normality Assessment via Histogram Analysis

In addition to skewness and kurtosis statistics, the normality of the data was further assessed visually through histogram analysis. The histograms for each construct are presented in Figures 11 to 17 respectively.

Figure 11

Histogram for AI Dependency

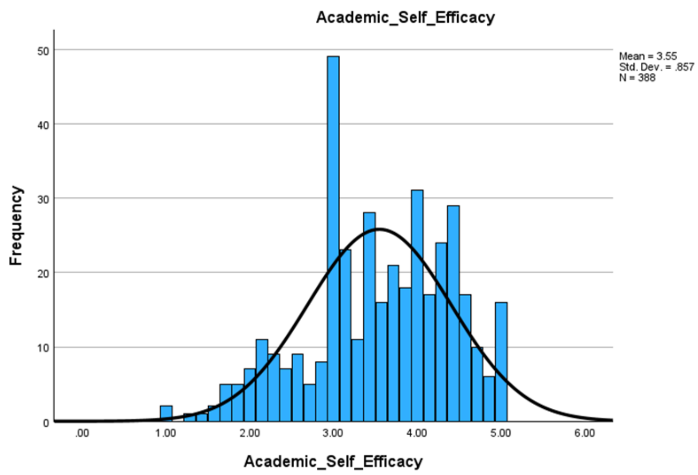


Note. Generated from SPSS software (Version 31)

The histogram for AI Dependency (Figure 11) showed a unimodal distribution with a slight left skew. The highest frequency occurred around the scores of 4.00 to 4.40, indicating that most respondents reported a moderately high level of AI Dependency

Figure 12

Histogram for Academic Self-Efficacy

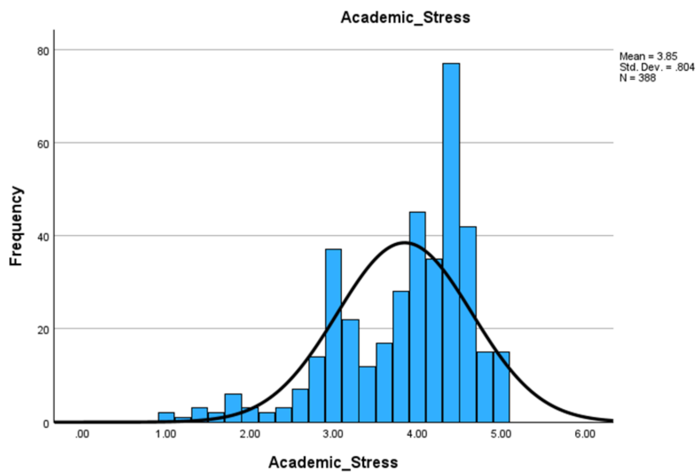


Note. Generated from SPSS software (Version 31)

Academic Self-Efficacy (Figure 12) displayed a relatively symmetrical unimodal distribution, with the peak frequency concentrated between 3.00 and 4.43. This suggests that respondents generally possessed a moderate to high level of academic self-efficacy.

Figure 13

Histogram for Academic Stress

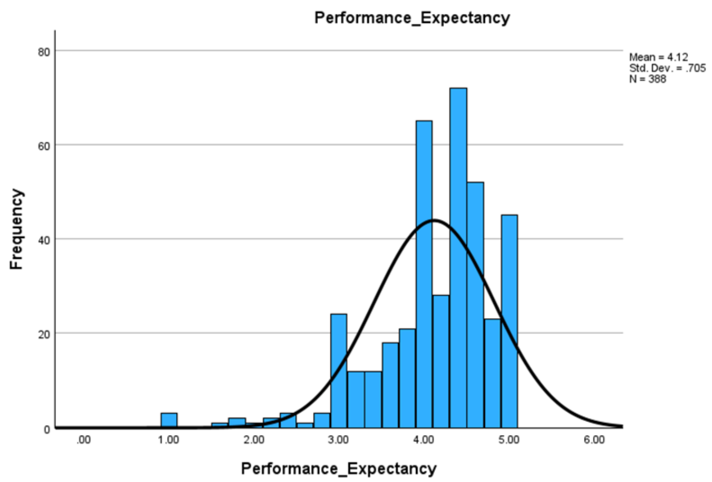


Note. Generated from SPSS software (Version 31)

The histogram for Academic Stress (Figure 13) revealed a left-skewed distribution, with the highest frequencies observed at the upper end (around 4.00 to 4.60). This indicates that a considerable proportion of respondents experienced higher levels of academic stress.

Figure 14

Histogram for Performance Expectancy

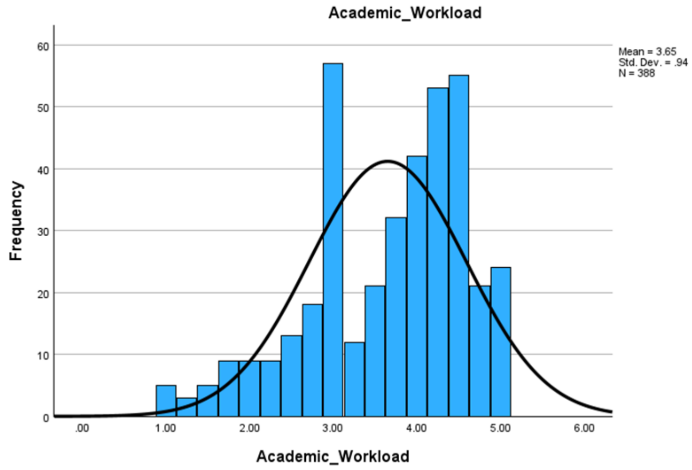


Note. Generated from SPSS software (Version 31)

Performance Expectancy (Figure 14) showed a unimodal distribution with a moderate left skew. The distribution peaked around 4.00 to 4.60, suggesting that most respondents held positive performance expectancy toward GenAI.

Figure 15

Histogram for Academic Workload

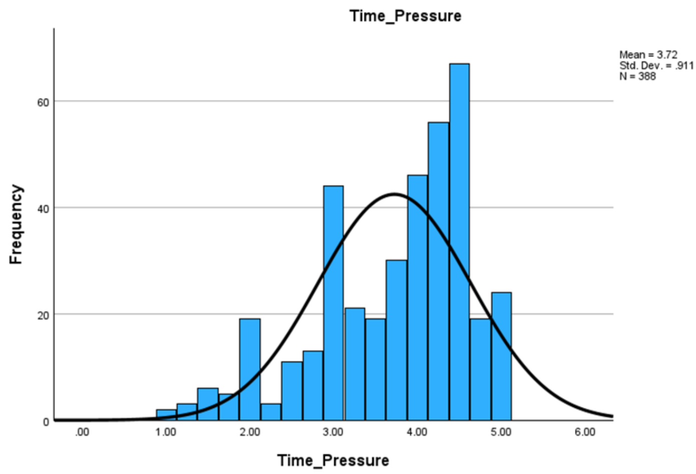


Note. Generated from SPSS software (Version 31)

Academic Workload (Figure 15) exhibited a unimodal distribution slightly skewed to the left, with the highest frequencies between 3.75 and 4.50. This reflects that respondents generally perceived a moderate to high academic workload.

Figure 16

Histogram for Time Pressure

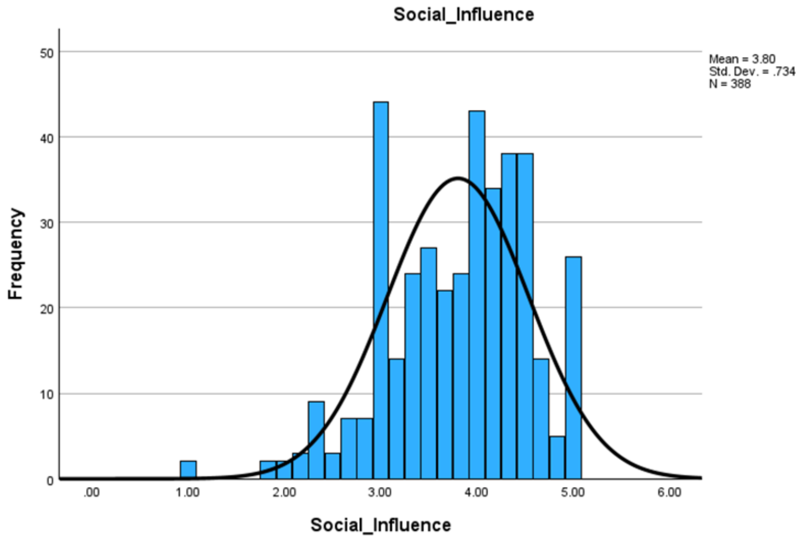


Note. Generated from SPSS software (Version 31)

Time Pressure (Figure 16) also displayed a left-skewed unimodal distribution, peaking around 4.00 to 4.50. A large number of respondents reported experiencing relatively high time pressure.

Figure 17

Histogram for Social Influence



Note. Generated from SPSS software (Version 31)

Finally, the histogram for Social Influence (Figure 17) showed a unimodal distribution with a slight left skew. The frequencies were highest between 3.83 and 4.50, indicating moderate to strong social influence on GenAI usage among the respondents.

4.4 Inferential Analysis

4.4.1 Pearson Correlation Analysis

4.4.1.1 Academic Self-Efficacy with AI Dependency (Hypothesis 1)

H_0: There is no significant relationship between academic self-efficacy and AI dependency using GenAI among undergraduates in a Malaysian private university.

H_1: There is a significant relationship between academic self-efficacy and AI dependency using GenAI among undergraduates in a Malaysian private university.

Table 22

Correlation between Academic Self-Efficacy and AI Dependency

		AI Dependency
Academic Self-Efficacy	Pearson Correlation	0.006
	Sig. (2-tailed)	0.901
	N	388

Source: Generated from SPSS software (Version 31)

Table 22 shows that the correlation coefficient between ASE and AID is 0.006 ($p = 0.901$). This indicates a very weak positive relationship between ASE and AID. Since the p-value (0.901) is greater than the significance level of 0.05, the relationship is not statistically significant.

4.4.1.2 Academic Stress with AI Dependency (Hypothesis 2)

H_0: There is no significant relationship between academic stress and AI dependency using GenAI among undergraduates in a Malaysian private university.

H_1: There is a significant relationship between academic stress and AI dependency using GenAI among undergraduates in a Malaysian private university.

Table 23

Correlation between Academic Stress and AI Dependency

		AI Dependency
Academic Stress	Pearson Correlation	0.607
	Sig. (2-tailed)	<0.001
	N	388

Source: Generated from SPSS software (Version 31)

Table 23 shows that the correlation coefficient between AS and AID is 0.607 ($p < 0.001$). This suggests a moderate to strong positive relationship between AS and AID. As the p-value is less than 0.05, the relationship is statistically significant.

4.4.1.3 Performance Expectancy with AI Dependency (Hypothesis 3)

H_0: There is no significant relationship between performance expectancy and AI dependency using GenAI among undergraduates in a Malaysian private university.

H_1: There is a significant relationship between performance expectancy and AI dependency using GenAI among undergraduates in a Malaysian private university.

Table 24

Correlation between Performance Expectancy and AI Dependency

		AI Dependency
Performance Expectancy	Pearson Correlation	0.483
	Sig. (2-tailed)	<0.001
	N	388

Source: Generated from SPSS software (Version 31)

Table 24 shows that the correlation coefficient between PE and AID is 0.483 ($p < 0.001$). This suggests a moderate to strong positive relationship between PE and AID. As the p-value is less than 0.05, the relationship is statistically significant.

4.4.1.4 Academic Workload with AI Dependency (Hypothesis 4)

H_0: There is no significant relationship between academic workload and AI dependency using GenAI undergraduates in a Malaysian private university.

H_1: There is a significant relationship between academic workload and AI dependency using GenAI undergraduates in a Malaysian private university.

Table 25

Correlation between Academic Workload and AI Dependency

		AI Dependency
Academic Workload	Pearson Correlation	0.684
	Sig. (2-tailed)	<0.001
	N	388

Source: Generated from SPSS software (Version 31)

Table 2 shows that the correlation coefficient between AW and AID is 0.684 ($p < 0.001$). This suggests a moderate to strong positive relationship between AW and AID. As the p-value is less than 0.05, the relationship is statistically significant.

4.4.1.5 Time Pressure with AI Dependency (Hypothesis 5)

H_0: There is no significant relationship between time pressure and AI dependency using GenAI among undergraduates in a Malaysian private university.

H_1: There is a significant relationship between time pressure and AI dependency using GenAI among undergraduates in a Malaysian private university.

Table 26

Correlation between Time Pressure and AI Dependency

		AI Dependency
Time Pressure	Pearson Correlation	0.660
	Sig. (2-tailed)	<0.001
	N	388

Source: Generated from SPSS software (Version 31)

Table 26 shows that the correlation coefficient between TP and AID is 0.660 ($p < 0.001$). This suggests a moderate to strong positive relationship between TP and AID. As the p-value is less than 0.05, the relationship is statistically significant.

4.4.1.6 Social Influence with AI Dependency (Hypothesis 6)

H_0: There is no significant relationship between social influence and AI dependency using GenAI among undergraduates in a Malaysian private university.

H_1: There is a significant relationship between social influence and AI dependency using GenAI among undergraduates in a Malaysian private university.

Table 27

Correlation between Social Influence and AI Dependency

		AI Dependency
Social Influence	Pearson Correlation	0.545
	Sig. (2-tailed)	<0.001
	N	388

Source: Generated from SPSS software (Version 31)

Table 27 shows that the correlation coefficient between SI and AID is 0.545 ($p < 0.001$). This suggests a moderate to strong positive relationship between SI and AID. As the p-value is less than 0.05, the relationship is statistically significant.

4.4.2 Multiple Linear Regression Analysis

Table 28

R-Square Value's Model Summary

Model Summary

Model	R	R-Square	Adjusted R-Square	Std. Error of the Estimate
1	0.734	0.539	0.532	0.65199

Source: Generated from SPSS software (Version 31)

Table 28 presents that the multiple correlation coefficient (R) is 0.734, indicating a strong positive relationship between the six independent variables (ASE, AS, PE, AW, TP, SI) and the dependent variable (AID).

The R-square value of 0.539 reveals that the six independent variables collectively explain 53.9% of the variance in AI Dependency using GenAI among undergraduates in a Malaysian private university. The adjusted R-square value is 0.532, which is very close to the R-square. This suggests that the model is reasonably stable and not overly inflated by the number of predictors.

However, the remaining 46.1% of the variance (1 - 0.539) remains unexplained, indicating that other factors not included in this study may also play important roles in influencing students' AI Dependency.

Table 29

Analysis of Variance

ANOVA						
Model		**Sum of Squares**	**df**	**Mean Square**	**F**	**Significant**
1	Regression	189.308	6	31.551	74.222	<0.001
	Residual	161.961	381	0.425		
	Total	351.269	387			

Source: Generated from SPSS software (Version 31)

Table 29 presents that the overall model is statistically significant, $F(6, 381) = 74.222$, $p < 0.001$. This indicates that the six independent variables collectively explain a significant portion of the variance in AID among undergraduates in a Malaysian private university.

Since the p-value is less than the conventional significance level of 0.05, the null hypothesis is rejected, and the alternative hypothesis is accepted. In other words, at least one of the independent variables is a significant predictor of AID.

Table 30

The Estimate of Parameter

Coefficients						
		Unstandardized Coefficients		**Standardized Coefficients**		
Model		**B**	**Std. Error**	**Beta**	**t**	**Sig.**
1	(Constant)	0.208	0.233		0.891	0.374
	Academic Self-Efficacy	-0.113	0.041	-0.102	-2.758	0.006
	Academic Stress	0.129	0.067	0.109	1.935	0.054
	Performance Expectancy	0.150	0.062	0.111	2.435	0.015
	Academic Workload	0.365	0.064	0.360	5.736	<0.001
	Time Pressure	0.148	0.070	0.142	2.119	0.035
	Social Influence	0.191	0.063	0.147	3.020	0.003

Source: Generated from SPSS software (Version 31)

Regression Equation:

Y = a + b1X1 + b2X2 + b3X3 + b4X4 + b5X5 + b6X6

Y = AI Dependency

X1 = Academic Self-Efficacy

X2 = Academic Stress

X3 = Performance Expectancy

X4 = Academic Workload

X5 = Time Pressure

X6 = Social Influence

a = the intercept

b = the slope (coefficient of Xn)

Multiple Regression Equation:

AI Dependency = 0.208 + (-0.113) (ASE) + 0.129 (AS) + 0.150 (PE) + 0.365 (AW) + 0.148 (TP) + 0.191 (SI)

The standardised beta coefficients were examined to determine the relative contribution of each independent variable to AI Dependency after controlling for the effects of all other predictors in the model.

Highest Contribution

Academic Workload (AW) has the highest beta value (β = 0.360). This indicates that AW is the strongest predictor and makes the largest unique contribution to explaining the variance in AI Dependency among undergraduates in a Malaysian private university.

Second Highest Contribution

Social Influence (SI) recorded the second-highest beta value (β = 0.147), suggesting that it contributes the second most to AI Dependency after controlling for other variables.

Third Highest Contribution

Time Pressure (TP) has the third-highest beta value (β = 0.142). This shows that TP provides the third strongest unique contribution in predicting AI Dependency among undergraduates at a Malaysian private university.

Fourth Highest Contribution

Performance Expectancy (PE) contributes the fourth-highest beta value (β = 0.111). This indicates that PE has the fourth largest unique influence on AI Dependency after accounting for all other independent variables.

Fifth Highest Contribution

Academic Stress (AS) has the fifth-highest beta value (β = 0.109), reflecting its relatively moderate unique contribution to the variation in AI Dependency.

Lowest Contribution

Academic Self-Efficacy (ASE) has the lowest beta value (β = -0.102). Notably, ASE shows a negative relationship with AI Dependency, indicating that it makes the weakest (and inverse) unique contribution among all predictors in the model.

4.5 Chapter Summary

This chapter presented the descriptive statistics, reliability results, and assumption tests based on 388 valid responses. The data were reliable and met the required assumptions for further analysis. Inferential results will be discussed in the following chapter.

CHAPTER 5: DISCUSSION, CONCLUSION, AND IMPLICATIONS

5.0 Introduction

This chapter discusses the major findings of the study, interprets the results in relation to existing literature, and provides theoretical and practical implications. It also tackles the limitations of the research and offers recommendations for future studies. Finally, a conclusion is presented to summarise the overall contributions of this research.

5.1 Summary of Statistical Analysis

The results for descriptive analysis, reliability test, Pearson Correlation Coefficient, and Multiple Linear Regression are summarised and discussed in this part.

5.1.1 Summary of Descriptive Analysis

Table 31

Summary of Descriptive Analysis

Variables	Frequency	Percentage (%)	Cumulative Frequency	Cumulative Percentage (%)
Gender				
Male	123	31.7	123	31.7

Female	265	68.3	388	100.0
Age				
18 – 21	171	44.1	171	44.1
22 – 25	199	51.3	370	95.4
26 – 29	16	4.1	386	99.5
30 and above	2	0.5	388	100.0
UTAR Campus				
Kampar Campus	360	92.8	360	92.8
Sungai Long Campus	28	7.2	388	100.0
Faculty				
Faculty of Accountancy and Management (FAM)	14	3.6	14	3.6
Faculty of Arts and Social Science (FAS)	43	11.1	57	11.7
Faculty of Creative Industries (FCI)	7	1.8	64	16.5
Faculty of Education (FEd)	4	1.0	68	17.5
Faculty of Engineering and Green Technology (FEGT)	14	3.6	82	21.1
Faculty of Information and Communication Technology (FICT)	50	12.9	132	34.0

Faculty of Science (FSc)	43	11.1	175	45.1
Faculty of Chinese Studies (FCS)	17	4.4	192	49.5
Lee Kong Chian Faculty of Engineering and Science (LKC FES)	4	1.0	196	50.5
M. Kandiah Faculty of Medicine and Health Sciences (MK FMHS)	3	0.8	199	51.3
Teh Hong Piow Faculty of Business and Finance (THP FBF)	189	48.7	388	100.0
GenAI Usage Frequency				
1 - 2 times per week	59	15.2	59	15.2
3 - 5 times per week	114	29.4	173	44.6
Once per day	157	40.5	330	85.1
Multiple times per day	58	14.9	388	100.0
Main Purpose of GenAI Use				
Exam preparation (e.g., revision	48	12.4	48	12.4

summaries, practice questions)				
Assignment guidance (e.g., structuring assignments, project planning)	119	30.7	167	43.1
Daily study support (e.g. notetaking, summarisation of lecture materials)	47	12.1	214	55.2
Research assistance (e.g. finding sources, explaining research concepts)	49	12.6	263	67.8
Writing assistance (e.g. paraphrasing, grammar checking, improving academic writing)	45	11.6	308	79.4
Idea generation or brainstorming (e.g. essay topics, project ideas, outlining arguments)	61	15.7	369	95.1
Language translation (e.g. translating academic materials,	19	4.9	388	100.0

	multilingual explanations)

Source: Developed for the research

Table 31 showed a total of 388 respondents in this study. The number of female respondents is higher than the male respondents, which is 68.3%. Most of the respondents are between the ages of 22 to 25, which is 51.3%. About 92.8% of the respondents come from the UTAR Kampar campus, and there is 48.7% of the respondents come from Teh Hong Piow Faculty of Business and Finance.

5.1.2 Summary of Inferential Analysis

5.1.2.1 Reliability Test

Table 19 showed that the results for AID, ASE, AS, PE, AW, TP and SI are higher than 0.8 and have a excellent reliability level, which is 0.899, 0.925, 0.862, 0.889, 0.883, 0.881 and 0.843 respectively.

5.1.2.2 Multicollinearity Test

Table 20 shows the Tolerance values ranged from 0.271 to 0.891 and the VIF values ranged from 1.123 to 3.691. All Tolerance values were above 0.10 and all VIF values were below 5. These results indicate that multicollinearity was not a problem in this study. Therefore, the data satisfied the multicollinearity assumption and were suitable for multiple linear regression analysis.

5.1.2.3 Pearson Correlation Coefficient Analysis

Tables 23, 24, 25, 26, and 27 showed that AS, PE, AW, TP and SI (independent variables) have a significant relationship with AI dependency (dependent variable) as the p-value is less than the alpha value of 0.05. However, table 22 shows that ASE (independent variables) have a weak significant relationship with AI dependency (dependent variable) as the p-value is higher than the alpha value of 0.05. Besides, AW has gained the highest Pearson Correlation value in this study, which is 0.684, followed by TP, AS, SI, PE, and ASE with Pearson Correlation values of 0.660, 0.607, 0.545, 0.483 and 0.006 respectively. The positive results showed a positive relationship between all independent variables and the dependent variable.

5.1.2.4 Multiple Linear Regression Analysis

Table 28 presents that the multiple correlation coefficient (R) is 0.734, indicating a strong positive relationship between the six independent variables (ASE, AS, PE, AW, TP, SI) and the dependent variable (AID).

The R-square value of 0.539 reveals that the six independent variables collectively explain 53.9% of the variance in AI Dependency using GenAI among undergraduates in a Malaysian private university. The adjusted R-square value is 0.532, which is very close to the R-square. This suggests that the model is reasonably stable and not overly inflated by the number of predictors.

5.2 Discussion of Major Findings

This section interprets the major findings in relation to the six hypotheses. Results were examined using Pearson correlation (bivariate r-values) and multiple regression (p-values in parentheses, controlling for other variables).

The multiple linear regression analysis revealed that the six independent variables collectively explained 53.9% of the variance in AI Dependency ($R^2 = 0.539$, Adjusted $R^2 = 0.532$, $F(6, 381) = 74.222$, $p < 0.001$). This indicates that the model has moderate explanatory power in understanding undergraduates' dependency on GenAI.

Table 32

Summary of Pearson's Correlation Coefficient and Multiple Linear Regression for the Independent Variables and AI Dependency

	Hypothesis	Results	Outcomes
H1	There is a significant relationship between academic self-efficacy and AI dependency using GenAI among undergraduates in a Malaysian private university.	R-value = 0.006 p-value = 0.901 (β = -0.102) (p = 0.006)	Supported (negative)
H2	There is a significant relationship between academic stress and AI dependency using GenAI among undergraduates in a Mala ysian private university.	R-value = 0.607 p-value = <0.001 (β = 0.109) (p = 0.054)	Not Supported
H3	There is a significant relationship between performance expectancy and AI dependency using	R-value = 0.483 p-value = <0.001 (β = 0.111)	Supported

	GenAI among undergraduates in a Mala ysian private university.	(p = 0.015)	
H4	There is a significant relationship between academic workload and AI dependency using GenAI among undergraduates in a Malaysian private university.	R-value = 0.684 p-value = <0.001 (β = 0.360) (p = <0.001)	Supported
H5	There is a significant relationship between time pressure and AI dependency using GenAI among undergraduates in a Mala ysian private university.	R-value = 0.660 p-value = <0.001 (β = 0.142) (p = 0.035)	Supported
H6	There is a significant relationship between social influence and AI dependency using GenAI among undergraduates in a Mala ysian private university.	R-value = 0.545 p-value = <0.001 (β = 0.147) (p = 0.003)	Supported

Source: Developed for the research

5.2.1 Hypothesis 1: Academic Self-Efficacy with AI Dependency

Academic Self-Efficacy showed a significant negative relationship with AI Dependency (β = -0.102, p = 0.006). This means that undergraduates who have higher confidence in their own academic abilities are less likely to develop strong dependency on GenAI tools. Based on Social Cognitive Theory (Bandura, 1986), this finding reflects the principle that individuals with high self-efficacy approach academic challenges with persistence and independent effort, reducing their tendency to rely on external tools such as AI as a substitute for their own cognitive engagement.

This finding is consistent with past research conducted by Zhang et al. (2024), Estrada-Araoz et al. (2025), Zhai et al. (2024), and Hasanein and Sobaih (2023). Zhang et al. (2024) hypothesised and empirically investigated that ASE is negatively associated with AID, finding that self-efficacy serves as a protective psychological resource against problematic AI usage behaviour among university students. In addition, Estrada-Araoz et al. (2025) discovered that further AI dependence was connected to a diminished academic self-concept, with higher dependency correlated with psychological characteristics reflecting less academic confidence and self-belief. These results are further supported by Zhai et al. (2024) and Hasanein and Sobaih (2023), who reported that students with stronger self-belief in their academic capabilities engaged with GenAI tools more purposefully and were less prone to over-reliance. Collectively, these studies show a consistent pattern across different national and cultural contexts: students with lower academic self-efficacy are more prone to AI dependency, whereas those with higher self-belief are more likely to engage with GenAI tools in a purposeful and non-dependent manner.

5.2.2 Hypothesis 2: Academic Stress with AI Dependency

Academic Stress showed a strong positive correlation with AI Dependency ($r = 0.607$, $p < 0.001$), but the relationship became non-significant in the multiple regression model ($\beta = 0.109$, $p = 0.054$). Therefore, Hypothesis 2 is not supported. The non-significant direct effect observed in this study is consistent with past research conducted by Habiba et al. (2025), who also found that AS did not emerge as a significant direct predictor of AI dependency when other psychological variables were simultaneously included in the model; this finding closely parallels the present result.

However, this does not imply that AS plays no meaningful role in AI dependency. From a different perspective, Zhang et al. (2024) and Acosta-Enriquez et al. (2025) provide important insight by establishing academic stress as a significant mediator rather than a direct predictor.

Nevertheless, the unique contribution of AS disappeared after controlling for workload (AW) and time pressure (TP) in the study. A plausible reason is that AS may not directly cause AI dependency; instead, it operates indirectly through heightened workload and time pressure. When students feel overwhelmed, they first experience increased workload perception, which then drives them to use GenAI as a coping tool. This suggests that stress alone may not be sufficient to create dependency unless it is accompanied by heavy academic demands.

5.2.3 Hypothesis 3: Performance Expectancy with AI Dependency

Performance Expectancy was a significant positive predictor of AI Dependency ($\beta = 0.111$, $p = 0.015$), supporting Hypothesis 3. Students who believed that using GenAI would improve their academic performance, productivity, and efficiency were more likely to develop dependency on these tools. This finding is consistent with past research conducted by Abbas et al. (2024) and Zhang et al. (2024). Abbas et al. (2024) specifically found that the higher the performance expectations students held toward ChatGPT, the greater the ChatGPT dependency they exhibited, establishing a direct empirical link between performance-oriented beliefs and dependency formation. Besides that, Zhang et al. (2024) found that performance expectations served as a key mediating mechanism through which academic self-efficacy and stress translated into AI dependency, confirming the central role of performance beliefs in the dependency formation process.

This pattern is also consistent with the broader UTAUT literature on GenAI adoption. A study of Norwegian university students applying UTAUT2 found that performance expectancy emerged as the construct with the largest impact on behavioural intention to use ChatGPT, and this study extends that finding by demonstrating that PE does not merely predict adoption but also contributes to dependency (Grassini et al., 2024; Jang, 2024). The underlying reason may be that when students perceive tangible benefits such as faster task completion and better grades, they gradually integrate GenAI into their daily academic routines. Over time, this perceived usefulness transforms into habitual reliance. In a competitive private university setting in Malaysia, where academic grades significantly affect future opportunities, students may view GenAI as a strategic tool to gain an advantage, thereby increasing their dependency.

5.2.4 Hypothesis 4: Academic Workload with AI Dependency

Academic Workload emerged as the strongest predictor of AI Dependency ($\beta = 0.360$, $p < 0.001$). This is one of the most important findings in the study. Students who perceived their academic workload as heavy were significantly more likely to rely excessively on GenAI. This result is consistent with the past research conducted by Carino et al. (2024), Abbas et al. (2024), and Klimova and Pikhart (2025). Abbas et al. (2024) found that academic workload was among the primary factors driving students toward ChatGPT utilisation, with students facing heavier workloads demonstrating significantly higher rates of AI tool use, which over time contributed to dependency formation. Carino et al. (2024) found that when students are faced with excessive academic demands, they are more likely to adopt AI tools as a means of managing workload efficiently, which can contribute to the development of dependency behaviours over time.

When students are overwhelmed by numerous assignments, tight deadlines, and heavy course content, they naturally seek efficient solutions to manage their workload. GenAI offers quick assistance in writing, summarising, and idea generation, which reduces immediate pressure (Klimova & Pikhart, 2025). However, frequent use can lead to over-reliance and reduced independent learning. In Malaysian private universities, where students often take multiple courses simultaneously, this workload-dependency pathway appears particularly strong.

5.2.5 Hypothesis 5: Time Pressure with AI Dependency

Time Pressure was a significant positive predictor ($\beta = 0.142$, $p = 0.035$), supporting Hypothesis 5. Undergraduates who experienced greater time constraints and difficulty in meeting deadlines showed higher levels of AI Dependency. This result complements the finding for academic workload and further reinforces the role of situational academic pressures as captured by UTAUT in shaping dependency behaviour. This finding is consistent with the past research conducted by Cariño et al. (2024) and Abbas et al. (2024). Abbas et al. (2024) identified TP as factors that directly precipitate students' ChatGPT use, as time-constrained students demonstrate higher rates of AI tool engagement, and become a pattern that the present study extends to the outcome of dependency rather than mere usage.

The reason is straightforward, which TP creates an urgent need for fast assistance. GenAI allows students to complete tasks more quickly, which temporarily alleviates the stress of deadlines. This normalises the use of AI tools as an acceptable academic strategy, particularly when students perceive that their peers are also using such technologies to cope with similar constraints. However, repeated reliance on AI for time-saving purposes can gradually diminish students' own time management and planning skills, leading to deeper dependency.

5.2.6 Hypothesis 6: Social Influence with AI Dependency

Social Influence significantly predicted AI Dependency ($\beta = 0.147$, $p = 0.003$). Peer recommendations, social media influence, and academic community norms played a notable role in encouraging GenAI use and subsequent dependency. In the university environment, students are particularly influenced by observing their peers successfully using GenAI for assignments and achieving favourable results. Such observations help establish social norms that make heavy GenAI use appear normal and even desirable. This social validation appears to accelerate the transition from occasional use to habitual dependency.

The result is consistent with the UTAUT, which positions SI as a key determinant of technology adoption and usage behaviour (Venkatesh et al., 2003). While most prior studies have examined SI in relation to initial adoption intention, the present study extends the UTAUT framework by demonstrating its direct association with dependency on GenAI. This novel contribution highlights the important role of peer norms and academic culture in reinforcing dependency behaviours in a Malaysian private university.

5.2.7 Summary of Findings

Overall, the findings show that external pressures, particularly heavy Academic Workload as the strongest driver, along with Time Pressure, Social Influence, and Performance Expectancy, are the main contributors to AI Dependency. In contrast, Academic Self-Efficacy serves as a significant protective factor, while Academic Stress did not show a significant direct effect.

These results highlight that external and situational pressures, including heavy academic workload, time pressure, social influence, and performance expectancy, are the primary drivers of dependency on GenAI among Malaysian private university undergraduates. Academic Self-Efficacy, on the other hand, serves as an important internal buffer that reduces the likelihood of over-reliance on GenAI tools.

Notably, although academic workload and academic stress are conceptually related and both showed strong bivariate correlations with AI dependency, only academic workload remained a significant predictor in the regression model. This apparent contradiction can be explained by the distinct nature of the two constructs. Academic workload represents the objective volume, intensity, and complexity of academic tasks, which creates tangible demands that students must address immediately. Academic stress, however, reflects the subjective emotional response to those demands. When students face heavy workloads, they tend to turn to GenAI as a practical and efficient coping strategy regardless of their level of emotional stress. Thus, the sheer quantity and complexity of work appear to be a more direct situational driver of dependency than subjective stress alone once workload and time pressure are accounted for. This pattern suggests that academic stress may operate indirectly through these external demands rather than exerting a unique direct influence.

Collectively, these findings expand existing technology acceptance and dependency models by demonstrating the critical role of academic contextual factors (as captured by UTAUT) alongside psychological resources (as captured by SCT) in shaping GenAI over-reliance. In the competitive environment of Malaysian private universities, where students often manage multiple courses, tight deadlines, and strong peer norms, these situational pressures appear particularly salient in driving dependency behaviours.

5.3 Implications of the Study

5.3.1 Theoretical Implications

This study makes several important theoretical contributions to the literature on GenAI use and dependency in higher education. It extends the Unified Theory of Acceptance and Use of Technology (UTAUT) beyond its traditional focus on behavioural intention and adoption to the outcome of actual dependency. By demonstrating that PE, AW, TP, and SI significantly predict AID, the study broadens UTAUT's explanatory power. Also, the integration of UTAUT with Social Cognitive Theory (SCT) offers a more comprehensive framework that simultaneously accounts for situational factors and psychological mechanisms (ASE and AS). This combined approach addresses previous calls for multidimensional models in technology-related dependency research.

The study also makes a novel contribution by establishing social influence (SI) as a direct predictor of dependency rather than merely adoption intention. This highlights the role of peer norms and academic culture in sustaining GenAI reliance.

Finally, by examining these relationships in a Malaysian private university context, the research provides valuable non-Western and institution-specific insights, as it enhances the cross-cultural applicability of both UTAUT and SCT.

5.3.2 Managerial Implications

This study also provides several practical implications for stakeholders in Malaysian higher education. For universities, the findings can guide the development of policies, workshops, and also support systems that promote responsible GenAI use while preventing excessive dependency. Lecturers and academic staff can apply the results to design teaching strategies and assessment methods that foster critical thinking and reduce over-reliance on AI tools.

For students, the study highlights the importance of understanding how academic workload, time pressure, social influence, and self-efficacy shape their GenAI use. This will enable them to adopt more balanced and self-regulated approaches. On a broader level, the Ministry of Higher Education (MOHE) may use these insights to refine national guidelines on AI integration, ensuring that technological advancement aligns with the goals of academic integrity and long-term student development.

5.4 Limitations of the Study

This study has several limitations that should be acknowledged. First, the sample was drawn from only one private university (Universiti Tunku Abdul Rahman) using a combination of convenience and purposive sampling techniques. Although this approach enabled the collection of sufficient data from full-time undergraduates in faculties with high assignment-based workloads, it limits the generalisability of the findings to students in other public and private universities across Malaysia. In addition, there was an imbalance in campus representation, with 92.8% of respondents from the Kampar Campus and 7.2% from the Sungai Long Campus.

This imbalance resulted from the sampling approach adopted; however, the study specifically focused on faculties prone to heavy assignment-based workloads, which are common across both campuses.

Second, the cross-sectional design limits the study of causal relationships over time. As all data were collected at a single point in time, the study cannot capture how the determinants of GenAI dependency may evolve or change longitudinally.

Third, the reliance on self-reported questionnaires may introduce common method bias and social desirability bias, which could potentially affect the accuracy of the responses.

Lastly, the study is confined to the scope of six theoretically grounded independent variables (ASE, AS, PE, AW, TP, and SI) to examine crucial factors influencing AID. Although the proposed model explained 53.9% of the variance in AI dependency, other potentially relevant factors, such as perceived ease of use, digital literacy, fear of missing out, and personality traits, were not included. Nevertheless, this study serves as a useful guideline for other scholars to incorporate and test these additional variables in future research, thereby extending the current understanding of GenAI dependency among Malaysian undergraduates.

These limitations reflect the intended scope and objectives of the study. They outline avenues for future research to expand and verify the results.

5.5 Recommendations for Future Research

Future research could build upon and extend the findings of the present study in several meaningful directions. Longitudinal designs are strongly recommended to examine how GenAI dependency develops and evolves over time, particularly as students progress through different years of their undergraduate studies. In addition, comparative studies across public and private universities as well as different regions in Malaysia would significantly enhance the generalisability of the findings and provide deeper insights into contextual variations.

The adoption of mixed-methods approaches, including qualitative techniques such as in-depth interviews and focus group discussions, would complement the current quantitative results by offering richer understandings of students' lived experiences, motivations, and decision-making processes when engaging with GenAI tools.

Besides that, expanding the conceptual framework by incorporating additional individual, contextual, or cultural variables could further increase the explanatory power and comprehensiveness of the model.

Finally, investigating the long-term impacts of GenAI dependency on students' critical thinking skills, creativity, independent learning abilities, and overall academic outcomes would make valuable contributions to both theory and practice in higher education.

5.6 Conclusion

This study set out to examine the determinants of AI Dependency on Generative Artificial Intelligence (GenAI) among undergraduates in a Malaysian private university. The findings revealed that Academic Workload (AW) was the strongest predictor of AI Dependency (AID), followed by Social Influence (SI), Time Pressure (TP), and Performance Expectancy (PE). Academic Self-Efficacy (ASE) stood out as a significant protective factor, while Academic Stress (AS) did not exert a significant direct effect when other variables were controlled.

These results highlight the powerful influence of situational academic pressures and social norms in shaping students' reliance on GenAI tools, while also underscoring the protective role of students' confidence in their own academic abilities. By extending UTAUT from adoption intention to actual dependency behaviour and by incorporating SCT's psychological constructs, this study provides a more comprehensive theoretical framework for understanding GenAI dependency in higher education.

In conclusion, although GenAI offers substantial benefits in terms of efficiency, productivity, and learning support, the findings emphasise the importance of fostering balanced and responsible use. It is hoped that the insights from this research will assist policymakers, universities, lecturers, and students in Malaysia to harness the advantages of GenAI while preserving critical thinking, independent learning skills, as well as academic integrity. As generative AI continues to transform higher education, understanding and managing the factors that drive dependency will remain essential for supporting the long-term development of future graduates.

REFERENCES

Abbas, M., Jam, F. A., & Khan, T. I. (2024). Is it harmful or helpful? Examining the causes and consequences of generative AI usage among university students. *International Journal of Educational Technology in Higher Education*, *21*(1). https://doi-org.libezp2.utar.edu.my/10.1186/s41239-024-00444-7

Abubakar, S., Jeilani, A., & Yusuf, M. (2025). The role of over-reliance on AI in the negative consequences of student learning: The moderating effects of ethical concerns and institutional policies. *Cogent Education*, *12*(1). https://doi.org/10.1080/2331186x.2025.2591503

Acosta-Enriquez, B. G., Ballesteros, M. A. A., Guzman Valle, M. de los A., Angaspilco, J. E. M., Aquino Lalupú, J. del R., Jaico, J. L. B., Germán Reyes, N. C., Alarcón García, R. E., & Castillo, W. E. J. (2025). The mediating role of academic stress, critical thinking and performance expectations in the influence of academic self-efficacy on AI dependence: Case study in college students. *Computers and Education: Artificial Intelligence*, *8*. https://doi-org.libezp2.utar.edu.my/10.1016/j.caeai.2025.100381

Acosta-Enriquez, B. G., Ballesteros, M. A., Pérez, C. R. V., Jordan, O. H., Vergara, J. A. M., Acosta, R. M., Vargas, C. G. A. P. & Castillo, J. C. A. (2025). AI in academia: How do social influence, self-efficacy, and integrity influence researchers' use of AI models? *Social Sciences & Humanities Open*, *11*, 101274. https://doi.org/10.1016/j.ssaho.2025.101274

Al-Abyadh, M. H. A., & Abdel Azeem, H. A. H. (2022). Academic achievement: Influences of university students' self-management and perceived self-efficacy. *Journal of Intelligence*, *10*(3), 55. https://doi.org/10.3390/jintelligence10030055

Alem, D. D. (2020). An overview of data analysis and interpretations in research. *International Journal of Academic Research in Education and Review*, *8*(1), 1-27.

Al-Kumaim, N. H., Hassan, S. H., ~~Al-kumaim, N. H., Hassan, S. H.,~~ Mohammed, F., & Saleh, A. Y. (2025). Navigating GenAI in Malaysian Universities: Use, Problems, and Challenges. In *2025 5th International Conference on Emerging Smart Technologies and Applications (eSmarTA)* (pp. 1-7). IEEE.

Al-Mamary, Y. H. S., Siddiqui, M. A., Abdalraheem, S. G., Jazim, F., Abdulrab, M., Rashed, R. Q., ... & Aliyu Alhaji, A. (2024). Factors impacting Saudi students' intention to adopt learning management systems using the TPB and UTAUT integrated model. *Journal of Science and Technology Policy Management*, *15*(5), 1110-1141. https://doi.org/10.1108/JSTPM-04-2022-0068

Alshamy, A., Al-Harthi, A., & Abdullah, S. (2025). Perceptions of Generative AI Tools in Higher Education: Insights from Students and Academics at Sultan Qaboos University. *Education Sciences*. https://doi.org/10.3390/educsci15040501.

Alshater, M. (2022). Exploring the role of artificial intelligence in enhancing academic performance: A case study of ChatGPT. SSRN. https://doi.org/10.2139/ssrn.4312358

Altememy, H. A., Mohammed, B. A., Hsony, M. K., Hassan, A. Y., Mazhair, R., Dawood, I. I., ... & Sharif, H. R. (2023). The influence of the artificial intelligence capabilities of higher education institutions in Iraq on students' academic performance: The role of AI-based technology application as a mediator. *Eurasian Journal of Educational Research*, *104*(104), 267-282.

Ayuni. (2025, September 4). *AI in Education Driving Malaysia's Future-Ready Workforce - MIDA | Malaysian Investment Development Authority*. MIDA | Malaysian Investment Development Authority. https://www.mida.gov.my/ai-in-education-driving-malaysias-future-ready-workforce/

Baharin, A., Sahadun, N., Ramli, S., & Redzuan, N. (2025). Exploring the Adoption of Generative Artificial Intelligence by TVET Students: A UTAUT Analysis of Perceptions, Benefits, and Implementation Challenges. *Journal of Information Systems Engineering and Management*. https://doi.org/10.52783/jisem.v10i19s.3052.

Bandura, A. (1986). Social foundations of thought and action: A social cognitive theory. In *Englewood Cliffs, NJ* (Vol. 1986). Upper Saddle River, NJ: PrenticeHall.

Bello, I. (2023). Critical Issues in the Methods of Data Collection in Geoinformatics and Environmental Sciences. *INTERNATIONAL JOURNAL OF SOCIAL SCIENCES AND MANAGEMENT RESEARCH*. https://doi.org/10.56201/ijssmr.v9.no8.2023.pg18.28.

Bhati, K., & Sethy, T. (2022). Self-efficacy: Theory to educational practice. *The International Journal of Indian Psychology*, *10*(1), 1123-1128.

Bhuiyan, M. A., Rahman, M. K., Basile, V., Ping, H., & Bari, A. M. (2025). Adoption of ChatGPT for students' learning effectiveness. *The International Journal of Management Education*, *23*(3), 101255.

Bick, A., Blandin, A., & Deming, D. (2024). The rapid adoption of generative AI. In *National Bureau of Economic Research*. https://doi.org/10.3386/w32966

Bittle, K., & El-Gayar, O. (2025). Generative AI and Academic Integrity in Higher Education: A Systematic Review and Research Agenda. *Information*, *16*(4), 296. https://doi-org.libezp2.utar.edu.my/10.3390/info16040296

Bouteraa, M. (2024). Understanding the diffusion of AI-generative (ChatGPT) in higher education: Insights from UTAUT and social cognitive theory. Computers in Human Behavior Reports. https://doi.org/10.1016/j.chbr.2024.100402

Bukhari, S. R., Batool, S., Shahab, I., Jalil, R., Arshad, A., Zahra, S. Q., ... & Khan, N. (2025). Role of AI Dependency in Psychological Distress and Academic Performance Among University Students. *International Journal of Social Sciences Bulletin*, *3*(3), 286-294.

Carino, K.J. C., Casimino, P. E. N., Castro, A. A. Y. & Caterio, C. L. C. (2024). the impact of academic workload, time pressure, and performance expectations on chatgpt utilization and dependence: a structural equation model. University of Santo Tomas College of Nursing.

Casimiro, P. E. (2024). The impact of academic workload, time pressure, and performance expectations on ChatGPT utilization and dependence: A structural equation model [Unpublished undergraduate thesis]. University of Santo Tomas. https://www.researchgate.net/publication/391677656

Chan, C. K. Y., & Hu, W. (2023). Students' voices on generative AI: Perceptions, benefits, and challenges in higher education. *International journal of educational technology in higher education*, *20*(1), 43.

Chou, C.-M., Shen, T.-C., & Shen, C.-H. (2022). Influencing factors on students' learning effectiveness of AI-based technology application: Mediation variable of the human-computer interaction experience. Education and Information Technologies, 27(6), 8723–8750. https://doi.org/10.1007/s10639-021-10866-9

Cooksey, R. W. (2020). Descriptive statistics for summarising data. *Springer Singapore,* 61-139. https://link.springer.com/chapter/10.1007/978-981-15-2537-7_5

Creswell, J. W., & Creswell, J. D. (2017). *Research design: Qualitative, quantitative, and mixed methods approaches*. Sage publications.

Cui, Y., Liu, Z., Sun, Z., & Jin, J. (2023). Campus learning environment, the influence of psychological emotions during learning on self-learning efficacy. https://doi.org/10.1145/3606094.3606127

Dalati, S. (2018). Measurement and measurement scales. In *Modernizing the Academic Teaching and Research Environment: Methodologies and Cases in Business Research.* Cham: Springer International Publishing, 79-96.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS quarterly*, *13*(3), 319-340.

Deckker, D., & Sumanasekara, S. (2025). ChatGPT in Neurosurgical Practice and Education: Benefits, Risks, and Challenges. *International Journal of*

Research and Innovation in Social Science, *9*(5), 2142-2161. https://dx.doi.org/10.47772/IJRISS.2025.905000168

Deng, Y., & Liu, H. (2025). To overcome test anxiety in on-line assessment: unpacking the mediator roles of techno competencies, teacher support, self-efficacy, and autonomy. *BMC psychology*, *13*(1), 192. https://doi.org/10.1186/s40359-025-02545-y

Digital Education Council. (2024). *Global AI student survey 2024*. https://www.digitaleducationcouncil.com/post/what-students-want-key-results-from-dec-global-ai-student-survey-2024

Dogaru, M., Pisică, O., Popa, C. Ș., Răgman, A. A., & Tololoi, I. R. (2025). The perceived impact of artificial intelligence on academic learning. *Frontiers in artificial intelligence*, *8*, 1611183.

Dwivedi, Y. K., Kshetri, N., Hughes, L., Slade, E. L., Jeyaraj, A., Kar, A. K., Baabdullah, A. M., et al. (2023). "So what if ChatGPT wrote it?" Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy. *International Journal of Information Management, 71*, Article 102642. https://doi.org/10.1016/j.ijinfomgt.2023.102642

EduAdvisor. (2026). *Universiti Tunku Abdul Rahman (UTAR): 2026 Ranking & Courses*. https://eduadvisor.my/university/universiti-tunku-abdul-rahman-utar

Eshet, Y., & Margaliot, A. (2022). Does creative thinking contribute to the academic integrity of education students?. *Frontiers in Psychology*, *13*, 925195.

Freeman, J. (2025). *Student generative AI survey 2025*. Higher Education Policy Institute (HEPI). https://www.hepi.ac.uk/reports/student-generative-ai-survey-2025/

Gandhi, R., Parmar, A., Kagathara, J., Lakkad, D., Kakadiya, J., & Murugan, Y. (2024). Bridging the artificial intelligence (AI) divide: do postgraduate medical students outshine undergraduate medical students in AI readiness?. *Cureus*, *16*(8).

Gao, X. (2023). Academic stress and academic burnout in adolescents: a moderated mediating model. *Frontiers in Psychology, 14*. https://doi.org/10.3389/fpsyg.2023.1133706.

George, D., and Mallery, M. (2003). Using SPSS for Windows step by step: a simple guide and reference.

Goh, A. Y., Hartanto, A., & Majeed, N. M. (2025). Generative artificial intelligence dependency: Scale development, validation, and its motivational, behavioral, and psychological correlates. *Computers in Human Behavior Reports*, 100845.

Gottems, L. B. D., Carvalho, E. M. P. D., Guilhem, D., & Pires, M. R. G. M. (2018). Good practices in normal childbirth: reliability analysis of an instrument by Cronbach's Alpha. *Revista Latino-Americana de Enfermagem*, *26*, e3000.

Grassini, S., Aasen, M., & Møgelvang, A. (2024). Understanding University Students' Acceptance of ChatGPT: Insights from the UTAUT2 Model. *Applied Artificial Intelligence, 38*. https://doi.org/10.1080/08839514.2024.2371168.

Greco, A., Annovazzi, C., Palena, N., Camussi, E., Rossi, G., & Steca, P. (2022). Self efficacy beliefs of university students: Examining factor validity and measurement invariance of the new academic self-efficacy scale. Frontiers in Psychology, 12. https://doi.org/10.3389/fpsyg.2021.498824.

Guo, F., Zhang, L., Shi, T., & Coates, H. (2025). Whether and When Could Generative AI Improve College Student Learning Engagement?. *Behavioral Sciences*, *15*(8), 1011.

Guo, S., Zheng, Y., & Zhai, X. (2024). Artificial intelligence in education research during 2013–2023: A review based on bibliometric analysis. *Education and information technologies*, *29*(13), 16387-16409.

Gusy, B., Lesener, T., & Wolter, C. (2021). Time Pressure and Health-Related Loss of Productivity in University Students: The Mediating Role of Exhaustion. Frontiers in public health, 9, 653440. https://doi.org/10.3389/fpubh.2021.653440

Hakim, A. L., Fajri, M. B., & Faizah, E. N. (2022). Evaluation Of Implementation Of MBKM: Does Academic Stress Affect Student Learning Outcomes? International Journal of Educational Research & Social Sciences, 3(1), 1-16. doi:10.51601/ijersc.v3i1.246

Hasanein, A. M., & Sobaih, A. E. E. (2023). Drivers and Consequences of CHATGPT use in Higher Education: Key Stakeholder Perspectives. *European Journal of Investigation in Health Psychology and Education*, *13*(11), 2599–2614. https://doi.org/10.3390/ejihpe13110181

Hasebrook, J. P., Michalak, L., Kohnen, D., Metelmann, B., Metelmann, C., Brinkrolf, P., et al. (2023). Digital transition in rural emergency medicine: Impact of job satisfaction and workload on communication and technology acceptance. *PLoS ONE, 18*(1), e0280956. https://doi.org/10.1371/journal.pone.0280956

He, A. J., Zhang, Z., Anand, P., & McMinn, S. (2024). Embracing generative artificial intelligence tools in higher education: a survey study at the Hong Kong University of Science and Technology. *Journal of Asian Public Policy*, *18*(2), 352–376. https://doi.org/10.1080/17516234.2024.2447195

Hitzig, N. B. (2004). Elements of sampling: the population, the frame, and the sampling unit. *The CPA Journal*, *74*(11), 30.

Hossan, D., Wolfs, B., & Petkovic, M. (2025). Questionnaire validity and reliability: A review with practical guidelines. *Journal of Entrepreneurship, Business and Economics*, *13*(1), 135-186.

Hu, K. (2023, February 2). ChatGPT sets record for fastest-growing user base. *Reuters*. https://www.reuters.com/technology/chatgpt-sets-record-fastest-growing-user-base-analyst-note-2023-02-01/

Huang, F. (2022). Data processing. In *Encyclopedia of big data.* Cham: Springer International Publishing, 312-316.

Jaaskelainen, T., Lopez-Iniguez, G., & Phillips, M. (2022). Music students' experienced workload in higher education: A systematic review and recommendations for good practice. Musicae Scientiae, 27(3), 102986492210939. https://doi.org/10.1177/10298649221093976

Jamaluddin, F., Jamaluddin, A. H., Jamaluddin, F., & Jamaluddin, F. (2025). Malaysia's AI-Driven Education Landscape: Policies, Applications, and Comparative Insights for a Digital Future. *arXiv preprint arXiv:2509.21858*.

Jang, M. (2024). AI Literacy and Intention to Use Text-Based GenAI for Learning: The Case of Business Students in Korea. *Informatics, 11*, 54. https://doi.org/10.3390/informatics11030054.

Jia, W., Pan, L., & Neary, S. (2025). Effect of GenAI Dependency on University Students' Academic Achievement: The Mediating Role of Self-Efficacy and Moderating Role of Perceived Teacher Caring. *Behavioral Sciences*, *15*(10), 1348.

Joa, C. Y., & Magsamen-Conrad, K. (2022). Social influence and UTAUT in predicting digital immigrants' technology use. *Behaviour & Information Technology*, *41*(8), 1620-1638. https://doi.org/10.1080/0144929X.2021.1892192

Kasneci, E., Seßler, K., Küchemann, S., Bannert, M., Dementieva, D., Fischer, F., Gasser, U., ... & Kasneci, G. (2023). ChatGPT for good? On opportunities and challenges of large language models for education. *Learning and Instruction, 101*, 102733. https://doi.org/10.1016/j.learninstruc.2023.102733

Ke, Q., Gong, Y., & Ke, C. (2025). Bridging AI literacy and UTAUT constructs: structural equation modeling of AI adoption among Chinese university students. *Humanities and Social Sciences Communications*, 12. https://doi.org/10.1057/s41599-025-05775-y.

Keedle, H., & Dahlen, H. (2023). Incorporating co-design principles and social media strategies to enhance cross-sectional online survey participation: The Birth Experience Study.. *Journal of nursing scholarship: an official publication of Sigma Theta Tau International Honor Society of Nursing*. https://doi.org/10.1111/jnu.12945.

Kim, J., Klopfer, M., Grohs, J. R., Eldardiry, H., Weichert, J., Cox, L. A., & Pike, D. (2025). Examining faculty and student perceptions of generative AI in university courses. *Innovative Higher Education*, *50*(4), 1281-1313.

Klimova, B., & Pikhart, M. (2025). Exploring the effects of artificial intelligence on student and academic well-being in higher education: A mini-review. *Frontiers in Psychology, 16*, Article 1498132. https://doi.org/10.3389/fpsyg.2025.1498132

Korchak, A., Al Murshidi, G., Getman, A., Raouf, N., Arshe, M., Al Meheiri, N., ... & Costley, J. (2025). The role of social influence in generative artificial intelligence ChatGPT adoption intentions among undergraduate and graduate students. *Innovations in Education and Teaching International*, *62*(5), 1559-1573. https://doi.org/10.1080/0309877X.2025.2496942

Kotronoulas, G., Miguel, S., Dowling, M., Fernández-Ortega, P., Colomer-Lahiguera, S., Bagcivan, G., Pape, E., Drury, A., Semple, C., Dieperink, K., & Papadopoulou, C. (2023). An Overview of the Fundamentals of Data Management, Analysis, and Interpretation in Quantitative Research.. *Seminars in oncology nursing*, 151398. https://doi.org/10.1016/j.soncn.2023.151398.

Koudela-Hamila, S., Santangelo, P. S., Ebner-Priemer, U. W., & Schlotz, W. (2022). Under which circumstances does academic workload lead to stress? *Journal of Psychophysiology, 36*(3), 188–197. https://doi.org/10.1027/0269-8803/a000293

Krejcie, R.V., & Morgan, D.W., (1970). Determining Sample Size for Research Activities. Educational and Psychological Measurement.

Labrague, L. J. (2024). Examining the influence of social support and resilience on academic self-efficacy and learning outcomes in pre-licensure student nurses. *Journal of Professional Nursing*, *55*, 119-124. https://doi.org/10.1016/j.profnurs.2024.09.012

Laitinen, S., Christopoulos, A., Laitinen, P., & Nieminen, V. (2024). Relationships between self-efficacy and learning approaches as perceived by computer science students. In *Frontiers in Education. 9*(1181616). https://doi.org/10.3389/feduc.2024.1181616

Lakens, D. (2022). Sample size justification. *Collabra: psychology*, *8*(1), 33267.

Lalla, M. (2017). Fundamental characteristics and statistical analysis of ordinal variables: A review. *Quality & Quantity*, *51*(1), 435-458.

Lee, A. H. C. (2025). Use of Generative Artificial Intelligence among Selected Pre-University Business Students at a Private University in Malaysia. *Asia-Pacific Journal of Futures in Education and Society*, *4*(1), 1-20.

Lee, S. H., & Kim, E. (2022). Inferential statistics. In *Scholarly research in music* (pp. 165-182). Routledge.

Legatt, A. (2025, September 18). 90% of college students use AI: Higher ed needs AI fluency support now. *Forbes*. https://www.forbes.com/sites/avivalegatt/2025/09/18/90-of-college-students-use-ai-higher-ed-needs-ai-fluency-support-now/

Leiter, C., Zhang, R., Chen, Y., Belouadi, J., Larionov, D., Fresen, V., & Eger, S. (2024). Chatgpt: A meta-analysis after 2.5 months. *Machine Learning with Applications*, *16*, 100541.

Li, Z., Shi, J., Zhao, Y., Zhang, B., & Zhong, B. (2024). Indirect media effects on the adoption of artificial intelligence: The roles of perceived and actual knowledge in the influence of presumed media influence model. *Journal of Broadcasting & Electronic Media*, *68*(4), 581-600. https://doi.org/10.1080/08838151.2024.2377244

Lim, W. (2024). What Is Quantitative Research? An Overview and Guidelines. *Australasian Marketing Journal, 33*, 325 - 348. https://doi.org/10.1177/14413582241264622.

Liu, X., Liu, Y., Dai, Y., & Fu, J. (2026). Academic stress and university students' dependency on generative artificial intelligence: a multiple mediation model using PLS-SEM. *BMC psychology*.

Lu, Z., Li, P., Yin, M., & Wang, W. (2022). The Effects of AI-based Credibility Indicators on the Detection and Spread of Misinformation under Social Influence. *Proceedings of the ACM on Human-Computer Interaction*, *6*(CSCW2). https://doi-org.libezp2.utar.edu.my/10.1145/3555562

Lund, B., Mannuru, N. R., Teel, Z. A., Lee, T. H., Ortega, N. J., Simmons, S., & Ward, E. (2025, September). Student perceptions of AI-assisted writing and academic integrity: ethical concerns, academic misconduct, and use of generative AI in higher education. In *AI in Education* (Vol. 1, No. 1, p. 2). MDPI.

Matimbwa, H., & Ringo, C. (2025). The Role of Pilot Studies on Validity and Reliability of Social Science Research Instruments: A Systematic Review. *East African Journal of Education and Social Sciences*, *6*(5), 14-27.

Meng, J., & Dai, Y. (2021). Emotional support from AI chatbots: Should a supportive partner self-disclose or not? Journal of Computer-Mediated Communication, 26(4), 207–222. https://doi.org/10.1093/jcmc/zmab005

Meng, Q., & Zhang, Q. (2023). The influence of academic self-efficacy on university students' academic performance: The mediating effect of academic engagement. Sustainability, 15(7). https://doi.org/10.3390/su15075767

Menon, D., & Shilpa, K. (2023). "Chatting with ChatGPT": Analyzing the factors influencing users' intention to Use the Open AI's ChatGPT using the UTAUT model. *Heliyon*, *9*(11). https://doi.org/10.1016/j.heliyon.2023.e20962

Mittal, U., Sai, S., Chamola, V., & Sangwan, D. (2024). A comprehensive review on generative AI for education. *Ieee Access*, *12*, 142733-142759.

Moghavvemi, S., & Jam, F. A. (2025). Unraveling the influential factors driving persistent adoption of ChatGPT in learning environments. *Education and Information Technologies*, *30*(15), 22443–22470. https://doi.org/10.1007/s10639-025-13662-x

Mohamad Mozie, N., Ghazali, N., & Ali Husin, L. I. (2025). Adopting artificial intelligence in higher education: insights from the UTAUT framework on student intentions. *Advances in Business Research International Journal*, *11*(1), 71-79.

Mohammad, N. H., Zamri, N. A. K., Roni, M., Ab, S. N. I., Hadi, S. F. N. S., & Mahzan, S. (2025). Navigating AI Ethics in Malaysian Universities: Addressing Privacy, Integrity, and Bias. *International Journal of Research and Innovation in Social Science*, *9*(1), 2451-2465.

Mueller, C. W. (2004). Conceptualization, operationalization, and measurement. *The SAGE encyclopedia of social science research methods*, 162-166.

Mweshi, G. K., & Sakyi, K. (2020). Application of sampling methods for the research design. *Archives of Business Review. 8*(11), 180-193.

Narayan, K. G., Sinha, D. K., & Singh, D. K. (2023). Sampling techniques. In *Veterinary public health & epidemiology: Veterinary public health-epidemiology-zoonosis-one health.* Singapore: Springer Nature Singapore. 111-123. https://doi.org/10.1007/978-981-19-7800-5_12

Nikolic, S. (2024). A systematic literature review of attitudes, intentions and behaviours of teaching academics pertaining to AI and generative AI (GenAI) in higher education: An analysis of GenAI adoption using the UTAUT framework. Australasian Journal of Educational Technology. https://doi.org/10.14742/ajet.9643

Onyinyechukwu, N. N., Stella, N. N., Assumpta, M., & Happiness, N. (2024). Perspectives of Undergraduate Students on the Academic Workload and Suicidal thoughts at Nigerian University. Asian Journal of Education and Social Studies, 50(8), 91–99. https://doi.org/10.9734/ajess/2024/v50i81509

Palikhe, A., & Phuyal, S. (2025). Ethical Consideration on Editing of Data in Research. *PAAN Journal*, *31*, 1854-1872.

Pallivathukal, R. G., Soe, H. H. K., Donald, P. M., Samson, R. S., Ismail, A. R. H., & Ismail, A. R. H. I. H. (2024). ChatGPT for academic purposes: survey among undergraduate healthcare students in Malaysia. *Cureus*, *16*(1).

Parmaksız, I. (2022). The mediating role of personality traits on the relationship between academic self-efficacy and digital addiction. *Education and Information Technologies*, *27*(6), 8883–8902. https://doi.org/10.1007/s10639-022-10996-8

Raffaghelli, J. E., Rodríguez, M. E., Guerrero-Roldán, A. E., & Baneres, D. (2022). Applying the UTAUT model to explain the students' acceptance of an early warning system in Higher Education. *Computers & Education*, *182*, 104468. https://doi.org/10.1016/j.compedu.2022.104468

Rahman, M. M., & Watanobe, Y. (2023). ChatGPT for education and research: Opportunities, threats, and strategies. Applied Sciences, 13(9), 5783. https://doi.org/10.3390/app13095783

Rani, P. S., Rani, K. R., Daram, S. B., & Angadi, R. V. (2023). Is it feasible to reduce academic stress in Net-Zero Energy buildings? Reaction from ChatGPT. Annals of Biomedical Engineering, 1–3. https://doi.org/10.1007/s10439-023-03286-y

Rasul, T. (2023). The role of ChatGPT in higher education: Benefits, challenges, and future research directions. Journal of Applied Learning & Teaching, 6(1). https://doi.org/10.37074/jalt.2023.6.1.29

Ravšelj, D., Keržič, D., Tomaževič, N., Umek, L., Brezovar, N., Iahad, N. A., Abdulla, A. A., Akopyan, A., Segura, M. W. A., AlHumaid, J., Allam, M. F., Alló, M., Andoh, R. P. K., Andronic, O., Arthur, Y. D., Aydın, F., Badran, A., Balbontín-Alvarado, R., Saad, H. B., . . . Aristovnik, A. (2025). Higher education students' perceptions of ChatGPT: A global study of early reactions. *PLoS ONE*, *20*(2), e0315011. https://doi.org/10.1371/journal.pone.0315011

Rehman, A., Behere, R. K., Islam, M. S., Abbasi, F. A., & Imtiaz, A. (2024). Assessing the usage of ChatGPT on life satisfaction among higher education students: The moderating role of subjective health. Technology in Society, 102655–102655. https://doi.org/10.1016/j.techsoc.2024.102655

Schei, O. M., et al. (2024). Perceptions and use of AI chatbots among students in higher education. Education Sciences, 14(8), 922. https://www.mdpi.com/2227-7102/14/8/922

Schunk, D. H., & DiBenedetto, M. K. (2021). Self-efficacy and human motivation. In *Advances in motivation science* (Vol. 8, pp. 153-179). Elsevier. https://doi.org/10.1016/bs.adms.2020.10.001

Sekaran, U., & Bougie, R. (2016). *Research methods for business: A skill building approach*. john wiley & sons.

Sharef, N. M. (2025). Advancing with AI at the fore: AI paper case study—Malaysia (Version 2). International Science Council. https://council.science/wp-content/uploads/2025/02/AI-Paper-Case-Study-Malaysia_V2.pdf

Sharifnia, A. M., Kpormegbey, D. E., Thapa, D. K., & Cleary, M. (2026). A primer of data cleaning in quantitative research: Handling missing values and outliers. *Journal of Advanced Nursing*, *82*(1), 970-975.

Shen, Y., & Cui, W. (2024). Perceived support and AI literacy: The mediating role of psychological needs satisfaction. Frontiers in Psychology, 15, Article Scopus. https://doi.org/10.3389/fpsyg.2024.1415248

Smith, S. S. (2021). The Academic Workload. Shifting from Accounting Practitioner to Academia, 87–145. https://doi.org/10.1007/978-3-030-67546-2_5

Smolansky, A., Cram, A., Raduescu, C., Zeivots, S., Huber, E., & Kizilcec, R. F. (2023, July). Educator and student perspectives on the impact of generative AI on assessments in higher education. In *Proceedings of the tenth ACM conference on Learning@ Scale* (pp. 378-382).

Sok, S., & Heng, K. (2023). ChatGPT for Education and Research: A Review of Benefits and Risks. SSRN Electronic Journal, 3(1), 110–121. https://doi.org/10.2139/ssrn.4378735

Sousa, A. E., & Cardoso, P. (2025). Use of generative AI by higher education students. *Electronics*, *14*(7), 1258.

Sumandya, I. W., Widana, I. W., Hendra, R., Supian, S., Yusuf, M., Wijaya, H. A., & Safitri, R. A. (2025). Adoption of artificial intelligence in STEM learning: Examining the effects of performance, effort, and social factors. *Jurnal Ilmiah Ilmu Terapan Universitas Jambi*, *9*(4), 1341-1354. https://doi.org/10.22437/jiituj.v9i4.44475

Taber, K. S. (2018). The use of Cronbach's alpha when developing and reporting research instruments in science education. *Research in science education*, *48*(6), 1273-1296. https://doi.org/10.1007/s11165-016-9602-2

Taherdoost, H. (2021). Data collection methods and tools for research; a step-by-step guide to choose data collection technique for academic and business research projects. *International journal of academic research in management (IJARM)*, *10*(1), 10-38.

Talent Corporation Malaysia Berhad. (2024). *Impact study of artificial intelligence, digital and green economy on the Malaysian workforce: Volume 2 – Sector: Information and communications technology*. https://www.talentcorp.com.my/images/uploads/publication/199/Impact-Study-of-Artificial-Intelligence-Digital-and-Green-Economy-on-the-Malaysian-Workforce-Volume-2-Sector-Information-and-Communications-Technology-1747879475.pdf

Tamrin, S. I., Omar, N. F., Kamaruzaman, K. N., Zaghlol, A. K., & Aziz, M. R. A. (2024). Evaluating the Impact of AI Dependency on Cognitive Ability among Generation Z in Higher Educational Institutions: A Conceptual

Framework. *Information Management and Business Review*, *16*(3), 1027-1033.

Tan, C. N. L., Tee, M., & Koay, K. Y. (2024). Discovering students' continuous intentions to use ChatGPT in higher education: a tale of two theories. *Asian Education and Development Studies*, *13*(4), 356-372.

Tan, M. J. T., & Maravilla, N. M. a. T. (2024). Shaping integrity: why generative artificial intelligence does not have to undermine education. *Frontiers in Artificial Intelligence*, *7*, 1471224. https://doi.org/10.3389/frai.2024.1471224

Tang, X., Chen, S., Cheng, Y., Chawla, N. V., Metoyer, R., & Ambrose, G. A. (2025). Understanding Student Attitudes and Acceptability of GenAI Tools in Higher Ed: Scale Development and Evaluation. *arXiv preprint arXiv:2508.01926*.

Terblanche, N., & Kidd, M. (2022). Adoption factors and moderating effects of age and gender that influence the intention to use a non-directive reflective coaching chatbot. *Sage Open*, *12*(2), 21582440221096136. https://doi.org/10.1177/21582440221096136

Teubner, T., Flath, C. M., Weinhardt, C., Van Der Aalst, W., & Hinz, O. (2023). Welcome to the Era of ChatGPT et al. *Business & information systems engineering*, *65*(2), 95-101.

Tian, J., & Zhang, R. (2025). Learners' AI dependence and critical thinking: The psychological mechanism of fatigue and the social buffering role of AI literacy. *Acta Psychologica*, *260*, 105725. https://doi.org/10.1016/j.actpsy.2025.105725

Tossell, C. C., Tenhundfeld, N. L., Momen, A., Cooley, K., & De Visser, E. J. (2024). Student perceptions of ChatGPT use in a college essay assignment: Implications for learning, grading, and trust in artificial intelligence. *IEEE Transactions on Learning Technologies*, *17*, 1069-1081. https://doi.org/10.1109/TLT.2024.3355015

Turner, D. (2020). Sampling Methods in Research Design. *Headache: The Journal of Head and Face Pain*, 60. https://doi.org/10.1111/head.13707.

Universiti Tunku Abdul Rahman. (2025). Utar.edu.my. https://utar.edu.my/Introduction.php

Universiti Tunku Abdul Rahman. (2026). *UTAR climbs to #109 in Asia and #26 in Southeast Asia in QS Asia University Rankings 2026*. Universiti Tunku Abdul Rahman. https://news.utar.edu.my/awards/2025/Nov/10/01/01.html

Uppal, K., & Hajian, S. (2025). Students' perceptions of ChatGPT in higher education: A study of academic enhancement, procrastination, and ethical concerns. *European Journal of Educational Research*, *14*(1), 199-211. https://doi.org/10.12973/eu-jer.14.1.199

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view1. *MIS quarterly*, *27*(3), 425-478.

Wa-Mbaleka, S. (2019). The researcher as an instrument. In *World conference on qualitative research.* Cham: Springer International Publishing, 33-41.

Wang, C., Li, X., Liang, Z., Sheng, Y., Zhao, Q., & Chen, S. (2025). The Roles of Social Perception and AI Anxiety in Individuals' Attitudes Toward ChatGPT in Education. *International Journal of Human-Computer Interaction*, *41*(9), 5713–5730. https://doi-org.libezp2.utar.edu.my/10.1080/10447318.2024.2365453

Wang, C., Wang, H., Li, Y., Dai, J., Gu, X., & Yu, T. (2025). Factors influencing university students' behavioral intention to use generative artificial intelligence: Integrating the theory of planned behavior and AI literacy. *International Journal of Human–Computer Interaction*, *41*(11), 6649-6671. https://doi.org/10.1080/10447318.2024.2383033

Wang, F., Li, N., Cheung, A. C., & Wong, G. K. (2025). In GenAI we trust: An investigation of university students' reliance on and resistance to generative AI in language learning. International Journal of Educational Technology in Higher Education, 22(1), 59.

Wang, X., Xu, X., Zhang, Y., Hao, S., & Jie, W. (2024). Exploring the impact of artificial intelligence application in personalized learning environments: thematic analysis of undergraduates' perceptions in China. *Humanities and Social Sciences Communications*, *11*(1), 1-10.

Williams, R. T. (2023). The ethical implications of using generative chatbots in higher education. Frontiers in Education, 8, Article Scopus. https://doi.org/10.3389/feduc.2023.1331607

Willie, M. M. (2024). Population and target population in research methodology. Golden Ratio of Social Science and Education, 4(1), 75-79.

Wood, D., & Moss, S. H. (2024). Evaluating the impact of students' generative AI use in educational contexts. *Journal of Research in Innovative Teaching & Learning*, *17*(2), 152-167.

Wu, C. M., Schulz, E., Pleskac, T. J., & Speekenbrink, M. (2022). Time pressure changes how people explore and respond to uncertainty. *Scientific reports*, *12*(1), 4122. https://doi.org/10.1038/s41598-022-07901-1

Wu, F., Dang, Y., & Li, M. (2025). A systematic review of responses, attitudes, and utilization behaviors on generative AI for teaching and learning in higher education. *Behavioral Sciences*, *15*(4), 467.

Wu, X., Zhu, P., Zhang, J., Yin, M., & Wang, Y. (2026). ChatGPT's impact on student learning outcomes: a meta-analysis of 35 experimental studies. *Humanities and Social Sciences Communications*.

Xue, L., Rashid, A., & Ouyang, S. (2024). The Unified Theory of Acceptance and Use of Technology (UTAUT) in Higher Education: A Systematic Review. *SAGE Open*, 14. https://doi.org/10.1177/21582440241229570

Yang, C., Chen, A., & Chen, Y. (2021). College students' stress and health in the COVID-19 pandemic: The role of academic workload, separation from school, and fears of contagion. *PLoS ONE, 16*(2), e0246676. https://doi.org/10.1371/journal.pone.0246676

Yang, S. J., Ogata, H., Matsui, T., & Chen, N. S. (2021). Human-centered artificial intelligence in education: Seeing the invisible through the visible. *Computers and Education: Artificial Intelligence*, *2*, 100008. https://doi.org/10.1016/j.caeai.2021.100008

Yusoff, R., & Mohd Janor, R. (2014). Generation of an interval metric scale to measure attitude. *Sage Open*, *4*(1), 2158244013516768.

Zakaria, S. K. (2025). Challenges faced by students using ChatGPT: A qualitative study at private universities in Malaysia. *International Journal of Asian Social Science*, *15*(9), 277-287.

Zhai, C., Wibowo, S., & Li, L. D. (2024). The effects of over-reliance on AI dialogue systems on students' cognitive abilities: a systematic review. *Smart Learning Environments*, *11*(1), 28. https://doi.org/10.1186/s40561-024-00316-7

Zhang, H., & Pang, J. (2026). Generative AI dependence in higher education: A PLS-SEM examination of Chinese and Malaysian teachers through the I-PACE model. *Acta Psychologica*, *264*, 106480.

Zhang, L., & Xu, J. (2025). The paradox of self-efficacy and technological dependence: Unraveling generative AI's impact on university students' task completion. *The Internet and Higher Education*, *65*, 100978.

Zhang, S., Zhao, X., Zhou, T., & Kim, J. H. (2024). Do you have AI dependency? The roles of academic self-efficacy, academic stress, and performance expectations on problematic AI usage behavior. *International Journal of Educational Technology in Higher Education*, *21*(1), 34. https://doi.org/10.1186/s41239-024-00467-0

Zhong, W., Luo, J., & Lyu, Y. (2024). How Do Personal Attributes Shape AI Dependency in Chinese Higher Education Context? Insights from Needs Frustration Perspective. *PLoS ONE*, *19*(11), 1–17. https://doi-org.libezp2.utar.edu.my/10.1371/journal.pone.0313314

Zhu, Z., Qin, S., Yang, L., Dodd, A., & Conti, M. (2023). Emotion regulation tool design principles for arts and design university students. Procedia CIRP, 119, 115–120. https://doi.org/10.1016/j.procir.2023.03.085

Zumitzavan, V. (2026). Sample Selection Methods. In *Social Science Methodologies for Management Research: From Philosophy to Practice in the AI Era.* Singapore: Springer Nature Singapore, 79-95.

APPENDICES

Appendix A
Questionnaire

UNIVERSITI TUNKU ABDUL RAHMAN
THE HONG PIOW FACULTY OF BUSINESS AND FINANCE (THP FBF)
BACHELOR OF BUSINESS ADMINISTRATION (HONOURS)

Examining the Determinants of AI Dependency on Generative Artificial Intelligence (GenAI) among Undergraduates in a Malaysian Private University

Dear Respondents,

We are students of the Bachelor of Business Administration (Honours) from Universiti Tunku Abdul Rahman (UTAR). The purpose of this research is to examine the determinants of the AI dependency of generative artificial intelligence (GenAI) among undergraduates in a Malaysian private university.

There are EIGHT (8) sections in this questionnaire. Section A consists of demographic questions, while Sections B, C, D, E, F, G, and H cover the variables examined in this study. Please read the instructions carefully before responding, and ensure that you answer ALL questions in ALL sections. The completion of this questionnaire will take approximately 10 to 15 minutes.

Your response will be kept strictly **PRIVATE AND CONFIDENTIAL** and will be used only for **ACADEMIC PURPOSES**.

For any inquiries, please do not hesitate to contact us at wongxianxin@1utar.my.

Your assistance in completing this questionnaire is very much appreciated. Thank you for your participation.

Yours sincerely,
Wong Xian Xin 23ABB00927
Teo Xue Lin 22ABB03053

PERSONAL DATA PROTECTION NOTICE

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

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

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

a) For assessment of any application to UTAR

b) For processing any benefits and services

c) For communication purposes

d) For advertorial and news

e) For general administration and record purposes

f) For enhancing the value of education

g) For educational and related purposes consequential to UTAR

h) For replying any responds to complaints and enquiries

i) For the purpose of our corporate governance

j) For the purposes of conducting research/ collaboration

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

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

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

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

Consent:

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

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

3. You may access and update your personal data by writing to us at wongxianxin@1utar.my.

Acknowledgment of Notice

[ ] I have been notified and that I hereby understood, consented and agreed per UTAR above notice.

[ ] I disagree, my personal data will not be processed.

Section A: Demographic Profile

Please place a **tick "√"** for each of the following:

1. Gender:
    [ ] Male
    [ ] Female
2. Age:
    [ ] 18 – 21
    [ ] 22 – 25
    [ ] 26 – 29
    [ ] 30 and above
3. UTAR Campus:
    [ ] Kampar Campus
    [ ] Sungai Long Campus
4. Faculty:
    [ ] Faculty of Accountancy and Management (FAM)
    [ ] Faculty of Arts and Social Science (FAS)
    [ ] Faculty of Creative Industries (FCI)
    [ ] Faculty of Education (FEd)
    [ ] Faculty of Engineering and Green Technology (FEGT)
    [ ] Faculty of Information and Communication Technology (FICT)
    [ ] Faculty of Science (FSc)
    [ ] Faculty of Chinese Studies (FCS)
    [ ] Lee Kong Chian Faculty of Engineering and Science (LKC FES)
    [ ] M. Kandiah Faculty of Medicine and Health Sciences (MK FMHS)
    [ ] Teh Hong Piow Faculty of Business and Finance (THP FBF)
5. How frequently do you use GenAI tools per week?
    [ ] 1–2 times per week
    [ ] 3–5 times per week
    [ ] Once per day
    [ ] Multiple times per day

6. What do you mostly use GenAI tools for?

   [ ] Exam preparation (e.g., revision summaries, practice questions)

   [ ] Assignment guidance (e.g., structuring assignments, project planning)

   [ ] Daily study support (e.g. note-taking, summarisation of lecture materials)

   [ ] Research assistance (e.g. finding sources, explaining research concepts)

   [ ] Writing assistance (e.g. paraphrasing, grammar checking, improving academic writing)

   [ ] Idea generation or brainstorming (e.g. essay topics, project ideas, outlining arguments)

   [ ] Language translation (e.g. translating academic materials, multilingual explanations)

Section B: AI Dependency

AI dependency refers to habitual, uncontrollable reliance on generative AI tools for academic tasks, prioritising AI-generated responses over independent thinking.

Please indicate the extent to which you agree or disagree with each statement by circling one number per line on the 5-point Likert scale response framework in which {(1) = strongly disagree; (2) = disagree; (3) = neutral, (4) = agree; and (5) = strongly agree.}

1= Strongly Disagree

2= Disagree

3= Neutral

4= Agree

5= Strongly Agree

No.	Questions	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
1.	I feel anxious when I cannot use GenAI tools for my academic tasks.	1	2	3	4	5
2.	I rely excessively on GenAI to complete my academic assignments.	1	2	3	4	5
3.	I have difficulty performing academic tasks without GenAI support.	1	2	3	4	5
4.	I feel the need to use GenAI with increasing frequency to maintain my academic performance.	1	2	3	4	5
5.	I find it difficult to control the time I spend using GenAI tools.	1	2	3	4	5

Section C: Academic Self-Efficacy

Academic self-efficacy is a student's belief in their own ability to successfully complete academic tasks and overcome challenges in their studies.

No.	Questions	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
1.	I am confident in my ability to understand the most complex concepts presented in class.	1	2	3	4	5
2.	I am certain I can do an excellent job on assignments and examinations.	1	2	3	4	5
3.	I can master the skills being taught in my course.	1	2	3	4	5
4.	I am confident in my ability to learn course material independently.	1	2	3	4	5
5.	I can successfully complete all assigned tasks regardless of their difficulty.	1	2	3	4	5

6.	I am capable of achieving good academic result through my own merit.	1	2	3	4	5
7.	I can achieve my academic goals even when facing challenges.	1	2	3	4	5

Section D: Academic Stress

Academic stress is the pressure and anxiety from academic demands like exams, assignments, and performance expectations that impact students' motivation and coping.

No.	Questions	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
1.	I feel overwhelmed by the amount of academic work I have.	1	2	3	4	5
2.	I experience anxiety when facing academic deadlines.	1	2	3	4	5
3.	I worry about not being able to meet academic expectations.	1	2	3	4	5
4.	I feel pressure to maintain good academic performance.	1	2	3	4	5
5.	Academic stress affects my ability to concentrate.	1	2	3	4	5

Section E: Performance Expectancy

Performance expectancy is a cognitive belief that influences students' attitudes about their ability to succeed in education, based on the criteria set by teachers, institutions, or external expectations.

No.	Questions	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
1.	Using GenAI improves my academic performance.	1	2	3	4	5
2.	GenAI helps me complete my academic tasks more quickly.	1	2	3	4	5
3.	GenAI increases my academic productivity.	1	2	3	4	5
4.	Using GenAI makes my academic tasks more efficient.	1	2	3	4	5
5.	GenAI tools help me achieve better grades.	1	2	3	4	5

Section F: Academic Workload

Academic workload refers to the amount and complexity of academic tasks and responsibilities students are expected to complete within a given time, including coursework, assignments, and study hours.

No.	Questions	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
1.	My academic workload (lectures, assignments, examinations, etc.) is too heavy to control.	1	2	3	4	5
2.	I feel overloaded from organising the work my studies require.	1	2	3	4	5
3.	I feel overburdened due to the lack of a clear plan for managing my studies.	1	2	3	4	5
4.	The instructors give too much work to do, which makes it difficult to motivate myself to finish tasks.	1	2	3	4	5

Section G: Time Pressure

Time pressure refers to the stress or urgency experienced when the time available to complete tasks is perceived as insufficient, often affecting performance and decision-making.

No.	Questions	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
1.	I often struggle to allocate sufficient time to thoroughly prepare for my class projects (lectures, assignments, examinations, etc.) due to heavy academic workload.	1	2	3	4	5
2.	I find it challenging to allocate enough time for study-related tasks (reviewing lecture notes, completing assigned tasks, doing tutorials) while maintaining the quality and thoroughness required.	1	2	3	4	5
3.	I experience difficulty in consistently meeting submission deadlines for my assignments and projects due to overlapping academic commitments and time constraints.	1	2	3	4	5
4.	I frequently feel rushed or in a hurry to complete academic tasks and projects on time, leading to a sense of urgency when meeting deadlines.	1	2	3	4	5

Section H: Social Influence

Social influence refers to the general direction or pattern of change in attitudes, behaviours, or preferences within a society over time.

No.	**Questions**	**Strongly Disagree**	**Disagree**	**Neutral**	**Agree**	**Strongly Agree**
1.	Social media recommends using GenAI tools.	1	2	3	4	5
2.	My friends and family suggest using GenAI tools.	1	2	3	4	5
3.	I discuss GenAI tools with my classmates/friends.	1	2	3	4	5
4.	My research colleagues think I should use GenAI tools.	1	2	3	4	5
5.	My university is supportive and provides guidelines to help students use GenAI tools effectively in their research.	1	2	3	4	5
6.	My academic community supports the use of GenAI tools in research.	1	2	3	4	5

Appendix B

Pilot Study

Reliability Test

DV: AI Dependency

Case Processing Summary

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

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

Reliability Statistics

Cronbach's Alpha	N of Items
.711	5

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
Anxiety without GenAI	13.9667	7.344	.627	.591
Excessive reliance on GenAI	13.7000	8.838	.361	.708
Difficulty working without GenAI	14.1667	7.109	.736	.543
Increasing frequency of use	13.5000	10.534	.292	.722
Difficulty controlling usage time	14.4000	8.455	.374	.708

IV 1: Academic Self-Efficacy

Case Processing Summary

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

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

Reliability Statistics

Cronbach's Alpha	N of Items
.891	7

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
Confidence in complex concepts	22.8333	15.454	.659	.879
Confidence in exams/assignments	22.6333	15.551	.780	.864
Mastery of course skills	22.8333	15.523	.615	.886
Independent learning ability	22.7333	14.892	.693	.875
Handling difficult tasks	22.6000	16.386	.756	.869
Merit-based achievement	22.6333	16.654	.631	.881
Goal achievement under challenge	22.3333	16.299	.756	.869

IV 2: Academic Stress

Case Processing Summary

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

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

Reliability Statistics

Cronbach's Alpha	N of Items
.617	5

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
Overwhelmed by workload	16.4000	5.076	.275	.612
Deadline anxiety	16.0333	5.068	.367	.567
Fear of failing expectations	16.2333	4.254	.556	.463
Pressure to perform	16.2667	5.306	.269	.611
Stress affecting concentration	16.2667	4.271	.411	.543

IV 3: Performance Expectancy

Case Processing Summary

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

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

Reliability Statistics

Cronbach's Alpha	N of Items
.762	5

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
Improve academic performance	17.8333	3.316	.684	.679
Complete tasks faster	17.8000	2.924	.543	.720
Increase productivity	17.7667	3.082	.527	.723
Enhance task efficiency	17.6667	3.540	.533	.723
Achieve better grades	17.8667	3.430	.438	.752

IV 4: Academic Workload

Case Processing Summary

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

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

Reliability Statistics

Cronbach's Alpha	N of Items
.782	4

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
Workload beyond control	11.5000	4.397	.799	.615
Overloaded by study organization	11.2000	5.200	.637	.709
Lack of management plan	11.4667	4.671	.559	.751
Excessive instructor demands	11.4333	5.771	.400	.817

IV 5: Time Pressure

Case Processing Summary

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

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

Reliability Statistics

Cronbach's Alpha	N of Items
.826	4

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
Insufficient project prep time	12.0333	5.206	.741	.741
Struggle with study quality vs time	12.0000	5.103	.623	.799
Overlapping deadlines	11.8333	5.730	.667	.778
Feeling rushed to finish	11.8333	5.523	.596	.807

IV 6: Social Influence

Case Processing Summary

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

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

Reliability Statistics

Cronbach's Alpha	N of Items
.825	6

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
Social media influence	19.9667	12.861	.511	.815
Family/Friends suggestions	20.1000	13.266	.509	.814
Peer discussions	19.5000	15.293	.521	.821
Colleague expectations	19.8667	11.844	.775	.758
University support/guidelines	20.3000	11.114	.623	.796
Academic community support	20.1000	11.610	.727	.766

Appendix C

Descriptive Analysis

Demographic Profile: Gender

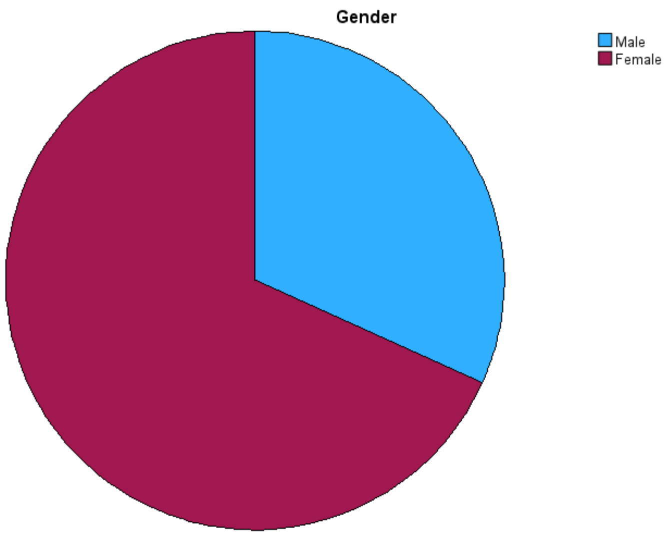
Statistics

Gender

N	Valid	388
	Missing	0
Mean		1.6830
Median		2.0000
Mode		2.00
Std. Deviation		.46591
Variance		.217
Range		1.00
Minimum		1.00
Maximum		2.00
Percentiles	25	1.0000
	50	2.0000
	75	2.0000

Gender

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Male	123	31.7	31.7	31.7
	Female	265	68.3	68.3	100.0
	Total	388	100.0	100.0	



Demographic Profile: Age

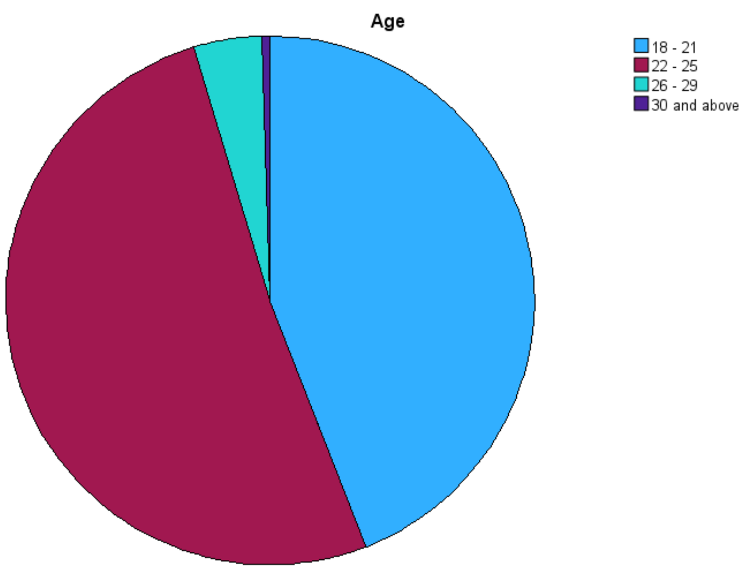
Statistics

Age

N	Valid	388
	Missing	0
Mean		1.6108
Median		2.0000
Mode		2.00
Std. Deviation		.59332
Variance		.352
Range		3.00
Minimum		1.00
Maximum		4.00
Percentiles	25	1.0000
	50	2.0000
	75	2.0000

Age

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	18 - 21	171	44.1	44.1	44.1
	22 - 25	199	51.3	51.3	95.4
	26 - 29	16	4.1	4.1	99.5
	30 and above	2	.5	.5	100.0
	Total	388	100.0	100.0	



Demographic Profile: UTAR Campus

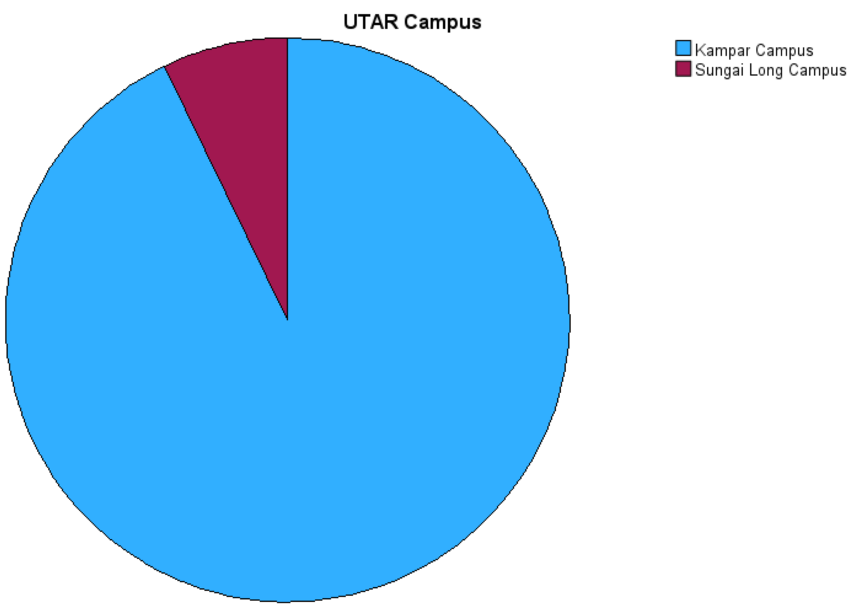
Statistics

UTAR Campus

N	Valid	388
	Missing	0
Mean		1.0722
Median		1.0000
Mode		1.00
Std. Deviation		.25909
Variance		.067
Range		1.00
Minimum		1.00
Maximum		2.00
Percentiles	25	1.0000
	50	1.0000
	75	1.0000

UTAR Campus

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Kampar Campus	360	92.8	92.8	92.8
	Sungai Long Campus	28	7.2	7.2	100.0
	Total	388	100.0	100.0	



Demographic Profile: Faculty

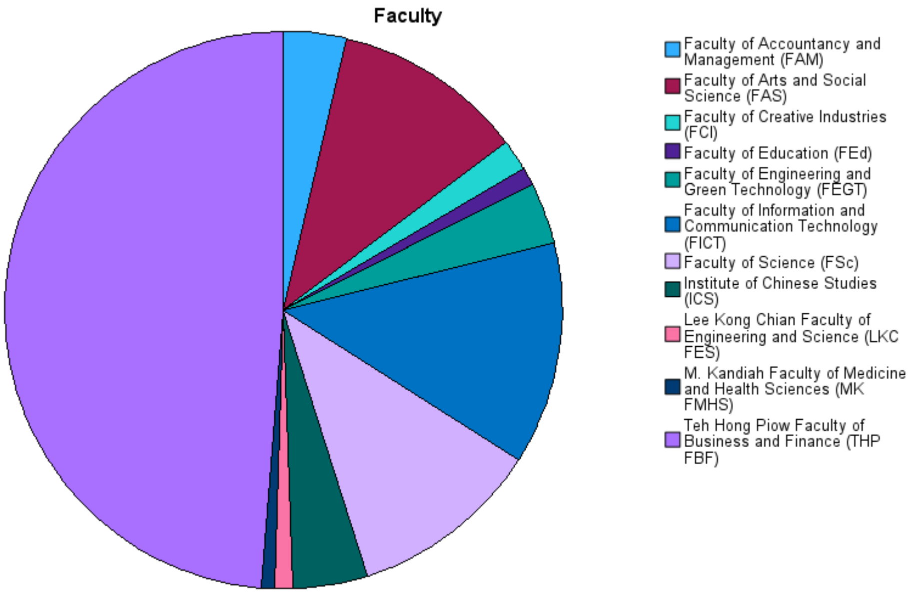
Statistics

Faculty

N	Valid	388
	Missing	0
Mean		7.9613
Median		9.0000
Mode		11.00
Std. Deviation		3.43203
Variance		11.779
Range		10.00
Minimum		1.00
Maximum		11.00
Percentiles	25	6.0000
	50	9.0000
	75	11.0000

Faculty

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Faculty of Accountancy and Management (FAM)	14	3.6	3.6	3.6
	Faculty of Arts and Social Science (FAS)	43	11.1	11.1	14.7
	Faculty of Creative Industries (FCI)	7	1.8	1.8	16.5
	Faculty of Education (FEd)	4	1.0	1.0	17.5
	Faculty of Engineering and Green Technology (FEGT)	14	3.6	3.6	21.1
	Faculty of Information and Communication Technology (FICT)	50	12.9	12.9	34.0
	Faculty of Science (FSc)	43	11.1	11.1	45.1
	Institute of Chinese Studies (ICS)	17	4.4	4.4	49.5
	Lee Kong Chian Faculty of Engineering and Science (LKC FES)	4	1.0	1.0	50.5
	M. Kandiah Faculty of Medicine and Health Sciences (MK FMHS)	3	.8	.8	51.3
	Teh Hong Piow Faculty of Business and Finance (THP FBF)	189	48.7	48.7	100.0
	Total	388	100.0	100.0	



Demographic Profile:: GenAI Usage Frequency

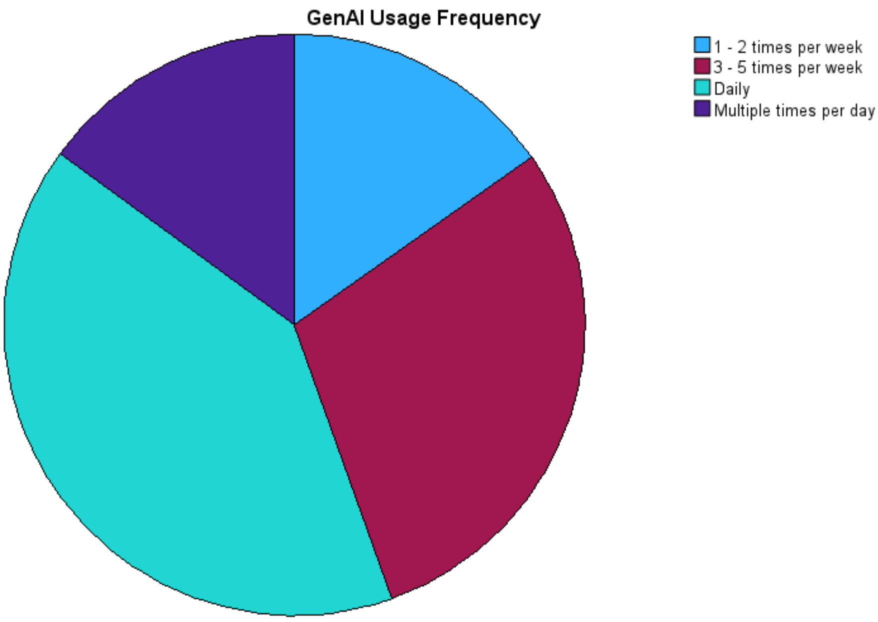
Statistics

GenAI Usage Frequency

N	Valid	388
	Missing	0
Mean		2.5515
Median		3.0000
Mode		3.00
Std. Deviation		.92338
Variance		.853
Range		3.00
Minimum		1.00
Maximum		4.00
Percentiles	25	2.0000
	50	3.0000
	75	3.0000

GenAI Usage Frequency

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1 - 2 times per week	59	15.2	15.2	15.2
	3 - 5 times per week	114	29.4	29.4	44.6
	Daily	157	40.5	40.5	85.1
	Multiple times per day	58	14.9	14.9	100.0
	Total	388	100.0	100.0	



Demographic Profile: Main Purpose of GenAI Use

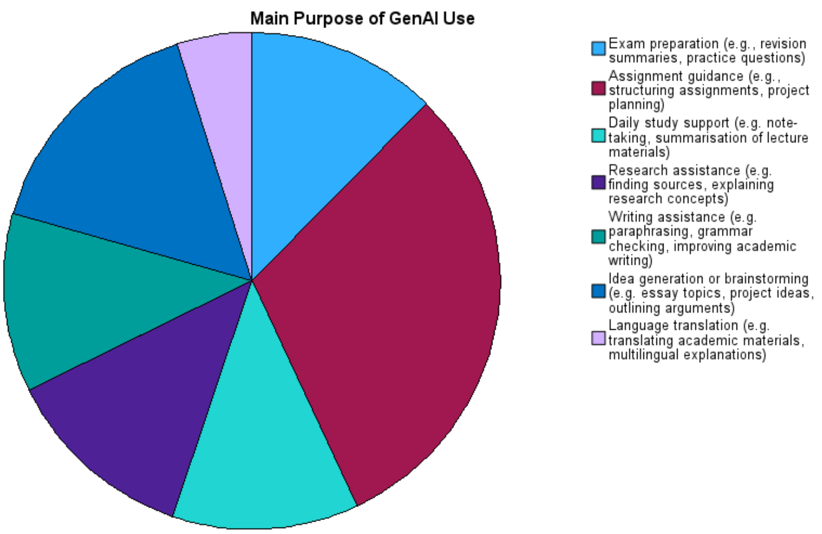
Statistics

Main Purpose of GenAI Use

N	Valid	388
	Missing	0
Mean		3.4716
Median		3.0000
Mode		2.00
Std. Deviation		1.83751
Variance		3.376
Range		6.00
Minimum		1.00
Maximum		7.00
Percentiles	25	2.0000
	50	3.0000
	75	5.0000

Main Purpose of GenAI Use

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Exam preparation (e.g., revision summaries, practice questions)	48	12.4	12.4	12.4
	Assignment guidance (e.g., structuring assignments, project planning)	119	30.7	30.7	43.0
	Daily study support (e.g. note-taking, summarisation of lecture materials)	47	12.1	12.1	55.2
	Research assistance (e.g. finding sources, explaining research concepts)	49	12.6	12.6	67.8
	Writing assistance (e.g. paraphrasing, grammar checking, improving academic writing)	45	11.6	11.6	79.4
	Idea generation or brainstorming (e.g. essay topics, project ideas, outlining arguments)	61	15.7	15.7	95.1
	Language translation (e.g. translating academic materials, multilingual explanations)	19	4.9	4.9	100.0
	Total	388	100.0	100.0	



Appendix D

Central Tendencies Measurement of Constructs

DV: AI Dependency

Descriptive Statistics

	N	Mean	Std. Deviation
Anxiety without GenAI	388	3.5644	1.04596
Excessive reliance on GenAI	388	3.6753	1.14016
Difficulty working without GenAI	388	3.5258	1.08161
Increasing frequency of use	388	3.7423	1.06655
Difficulty controlling usage time	388	3.1469	1.29262
Valid N (listwise)	388		

IV 1: Academic Self-Efficacy

Descriptive Statistics

	N	Mean	Std. Deviation
Confidence in complex concepts	388	3.3273	1.08719
Confidence in exams/assignments	388	3.5593	1.07068
Mastery of course skills	388	3.4253	1.03284
Independent learning ability	388	3.5335	1.08854
Handling difficult tasks	388	3.6134	.95372
Merit-based achievement	388	3.6469	.96800
Goal achievement under challenge	388	3.7216	1.01658
Valid N (listwise)	388		

IV 2: Academic Stress

Descriptive Statistics

	N	Mean	Std. Deviation
Overwhelmed by workload	388	3.7242	.96648
Deadline anxiety	388	4.0155	1.02917
Fear of failing expectations	388	3.8814	.97587
Pressure to perform	388	3.8918	.98497
Stress affecting concentration	388	3.7165	1.04772
Valid N (listwise)	388		

IV 3: Performance Expectancy

Descriptive Statistics

	N	Mean	Std. Deviation
Improve academic performance	388	4.0129	.83362
Complete tasks faster	388	4.1985	.88589
Increase productivity	388	4.1108	.84496
Enhance task efficiency	388	4.1778	.82080
Achieve better grades	388	4.0876	.84606
Valid N (listwise)	388		

IV 4: Academic Workload

Descriptive Statistics

	N	Mean	Std. Deviation
Workload beyond control	388	3.6289	.99684
Overloaded by study organization	388	3.7371	1.11042
Lack of management plan	388	3.6443	1.10778
Excessive instructor demands	388	3.5902	1.14779
Valid N (listwise)	388		

IV 5: Time Pressure

Descriptive Statistics

	N	Mean	Std. Deviation
Insufficient project prep time	388	3.6546	1.03644
Struggle with study quality vs time	388	3.7964	1.04290
Overlapping deadlines	388	3.6727	1.10371
Feeling rushed to finish	388	3.7680	1.06279
Valid N (listwise)	388		

IV 6: Social Influence

Descriptive Statistics

	N	Mean	Std. Deviation
Social media influence	388	4.0361	.95302
Family/Friends suggestions	388	3.8299	.94113
Peer discussions	388	3.8402	1.00399
Colleague expectations	388	3.7423	.97279
University support/guidelines	388	3.6649	1.00186
Academic community support	388	3.7036	1.01017
Valid N (listwise)	388		

Appendix E

Reliability Test

DV: AI Dependency

Case Processing Summary

		N	%
Cases	Valid	388	100.0
	Excluded[a]	0	.0
	Total	388	100.0

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

Reliability Statistics

Cronbach's Alpha	N of Items
.899	5

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
Anxiety without GenAI	14.0902	15.168	.789	.869
Excessive reliance on GenAI	13.9794	14.759	.757	.875
Difficulty working without GenAI	14.1289	14.934	.788	.869
Increasing frequency of use	13.9124	15.326	.746	.878
Difficulty controlling usage time	14.5077	14.261	.692	.894

IV 1: Academic Self-Efficacy

Case Processing Summary

		N	%
Cases	Valid	388	100.0
	Excluded[a]	0	.0
	Total	388	100.0

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

Reliability Statistics

Cronbach's Alpha	N of Items
.925	7

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
Confidence in complex concepts	21.5000	26.943	.697	.920
Confidence in exams/assignments	21.2680	25.985	.812	.908
Mastery of course skills	21.4021	26.644	.777	.912
Independent learning ability	21.2938	26.301	.762	.914
Handling difficult tasks	21.2139	27.631	.743	.916
Merit-based achievement	21.1804	27.140	.785	.912
Goal achievement under challenge	21.1057	26.782	.777	.912

IV 2: Academic Stress

Case Processing Summary

		N	%
Cases	Valid	388	100.0
	Excluded[a]	0	.0
	Total	388	100.0

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

Reliability Statistics

Cronbach's Alpha	N of Items
.862	5

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
Overwhelmed by workload	15.5052	11.077	.645	.842
Deadline anxiety	15.2139	10.479	.694	.830
Fear of failing expectations	15.3479	10.656	.715	.825
Pressure to perform	15.3376	10.762	.685	.832
Stress affecting concentration	15.5129	10.524	.668	.837

IV 3: Performance Expectancy

Case Processing Summary

		N	%
Cases	Valid	388	100.0
	Excluded[a]	0	.0
	Total	388	100.0

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

Reliability Statistics

Cronbach's Alpha	N of Items
.889	5

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
Improve academic performance	16.5747	8.245	.728	.866
Complete tasks faster	16.3892	7.995	.727	.867
Increase productivity	16.4768	8.131	.743	.863
Enhance task efficiency	16.4098	8.279	.735	.865
Achieve better grades	16.5000	8.204	.723	.867

IV 4: Academic Workload

Case Processing Summary

		N	%
Cases	Valid	388	100.0
	Excluded[a]	0	.0
	Total	388	100.0

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

Reliability Statistics

Cronbach's Alpha	N of Items
.883	4

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
Workload beyond control	10.9716	8.544	.788	.837
Overloaded by study organization	10.8634	8.103	.759	.845
Lack of management plan	10.9562	8.223	.737	.853
Excessive instructor demands	11.0103	8.165	.709	.866

IV 5: Time Pressure

Case Processing Summary

		N	%
Cases	Valid	388	100.0
	Excluded[a]	0	.0
	Total	388	100.0

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

Reliability Statistics

Cronbach's Alpha	N of Items
.881	4

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
Insufficient project prep time	11.2371	7.783	.766	.838
Struggle with study quality vs time	11.0954	7.978	.716	.857
Overlapping deadlines	11.2191	7.717	.709	.860
Feeling rushed to finish	11.1237	7.602	.777	.833

IV 6: Social Influence

Case Processing Summary

		N	%
Cases	Valid	388	100.0
	Excluded[a]	0	.0
	Total	388	100.0

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

Reliability Statistics

Cronbach's Alpha	N of Items
.843	6

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
Social media influence	18.7809	14.756	.512	.838
Family/Friends suggestions	18.9871	14.194	.612	.820
Peer discussions	18.9768	13.832	.613	.819
Colleague expectations	19.0747	13.599	.679	.806
University support/guidelines	19.1521	13.561	.658	.810
Academic community support	19.1134	13.496	.660	.810

Appendix F

Multicollinearity Test

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Social_Influence, Academic_Self_Efficacy, Performance_Expectancy, Academic_Workload, Academic_Stress, Time_Pressure[b]	.	Enter

a. Dependent Variable: AI_Dependency

b. All requested variables entered.

Coefficients[a]

Model		Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	Academic_Self_Efficacy	.891	1.123
	Academic_Stress	.381	2.626
	Performance_Expectancy	.583	1.714
	Academic_Workload	.307	3.254
	Time_Pressure	.271	3.691
	Social_Influence	.509	1.965

a. Dependent Variable: AI_Dependency

Appendix G

Normality Test

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
AI_Dependency	388	1.00	5.00	3.5309	.95272	-.676	.124	-.122	.247
Academic_Self_Efficacy	388	1.00	5.00	3.5468	.85706	-.407	.124	-.365	.247
Academic_Stress	388	1.00	5.00	3.8459	.80403	-1.048	.124	.892	.247
Performance_Expectancy	388	1.00	5.00	4.1175	.70495	-1.376	.124	2.875	.247
Academic_Workload	388	1.00	5.00	3.6501	.93981	-.709	.124	-.119	.247
Time_Pressure	388	1.00	5.00	3.7229	.91123	-.813	.124	-.019	.247
Social_Influence	388	1.00	5.00	3.8028	.73439	-.564	.124	.279	.247
Valid N (listwise)	388								

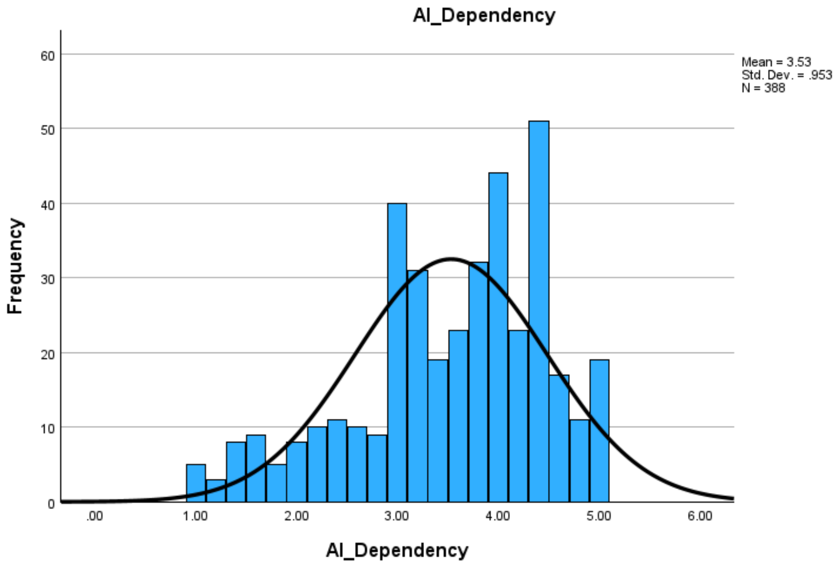
Appendix H

Normality Assessment via Histogram Analysis

DV: AI Dependency

AI_Dependency

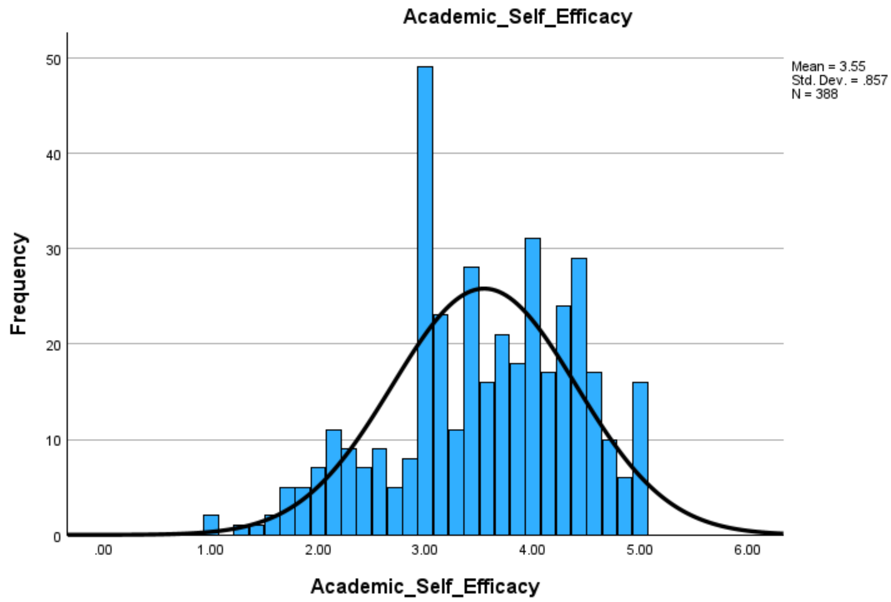
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1.00	5	1.3	1.3	1.3
	1.20	3	.8	.8	2.1
	1.40	8	2.1	2.1	4.1
	1.60	9	2.3	2.3	6.4
	1.80	5	1.3	1.3	7.7
	2.00	8	2.1	2.1	9.8
	2.20	10	2.6	2.6	12.4
	2.40	11	2.8	2.8	15.2
	2.60	10	2.6	2.6	17.8
	2.80	9	2.3	2.3	20.1
	3.00	40	10.3	10.3	30.4
	3.20	31	8.0	8.0	38.4
	3.40	19	4.9	4.9	43.3
	3.60	23	5.9	5.9	49.2
	3.80	32	8.2	8.2	57.5
	4.00	44	11.3	11.3	68.8
	4.20	23	5.9	5.9	74.7
	4.40	51	13.1	13.1	87.9
	4.60	17	4.4	4.4	92.3
	4.80	11	2.8	2.8	95.1
	5.00	19	4.9	4.9	100.0
	Total	388	100.0	100.0	



IV 1: Academic Self-Efficacy

Academic_Self_Efficacy

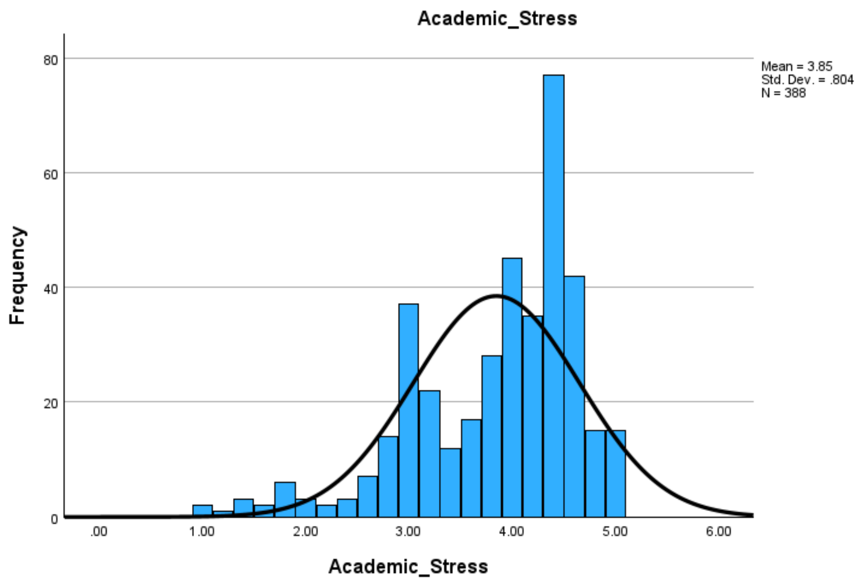
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1.00	2	.5	.5	.5
	1.29	1	.3	.3	.8
	1.43	1	.3	.3	1.0
	1.57	2	.5	.5	1.5
	1.71	5	1.3	1.3	2.8
	1.86	5	1.3	1.3	4.1
	2.00	7	1.8	1.8	5.9
	2.14	11	2.8	2.8	8.8
	2.29	9	2.3	2.3	11.1
	2.43	7	1.8	1.8	12.9
	2.57	9	2.3	2.3	15.2
	2.71	5	1.3	1.3	16.5
	2.86	8	2.1	2.1	18.6
	3.00	49	12.6	12.6	31.2
	3.14	23	5.9	5.9	37.1
	3.29	11	2.8	2.8	39.9
	3.43	28	7.2	7.2	47.2
	3.57	16	4.1	4.1	51.3
	3.71	21	5.4	5.4	56.7
	3.86	18	4.6	4.6	61.3
	4.00	31	8.0	8.0	69.3
	4.14	17	4.4	4.4	73.7
	4.29	24	6.2	6.2	79.9
	4.43	29	7.5	7.5	87.4
	4.57	17	4.4	4.4	91.8
	4.71	10	2.6	2.6	94.3
	4.86	6	1.5	1.5	95.9
	5.00	16	4.1	4.1	100.0
	Total	388	100.0	100.0	



IV 2: Academic Stress

Academic_Stress

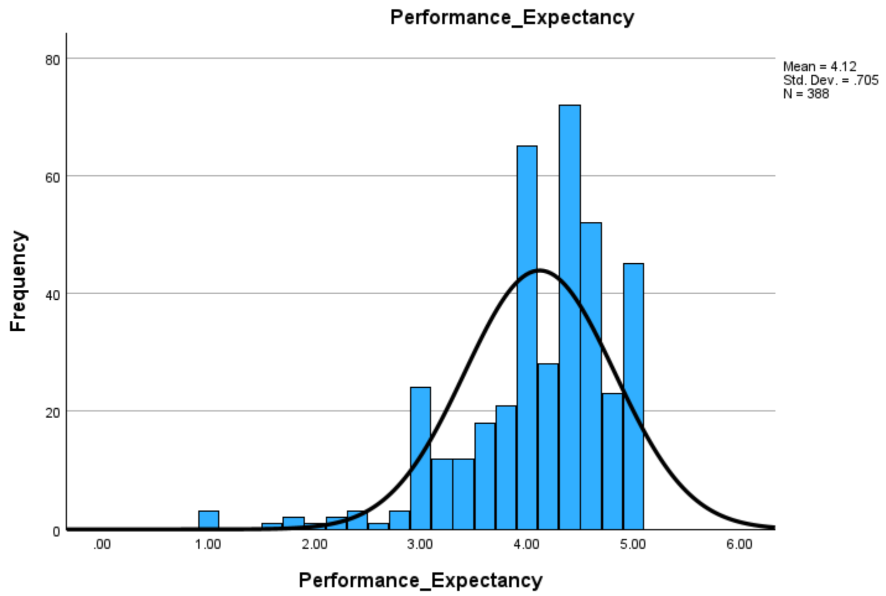
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1.00	2	.5	.5	.5
	1.20	1	.3	.3	.8
	1.40	3	.8	.8	1.5
	1.60	2	.5	.5	2.1
	1.80	6	1.5	1.5	3.6
	2.00	3	.8	.8	4.4
	2.20	2	.5	.5	4.9
	2.40	3	.8	.8	5.7
	2.60	7	1.8	1.8	7.5
	2.80	14	3.6	3.6	11.1
	3.00	37	9.5	9.5	20.6
	3.20	22	5.7	5.7	26.3
	3.40	12	3.1	3.1	29.4
	3.60	17	4.4	4.4	33.8
	3.80	28	7.2	7.2	41.0
	4.00	45	11.6	11.6	52.6
	4.20	35	9.0	9.0	61.6
	4.40	77	19.8	19.8	81.4
	4.60	42	10.8	10.8	92.3
	4.80	15	3.9	3.9	96.1
	5.00	15	3.9	3.9	100.0
	Total	388	100.0	100.0	



IV 3: Performance Expectancy

Performance_Expectancy

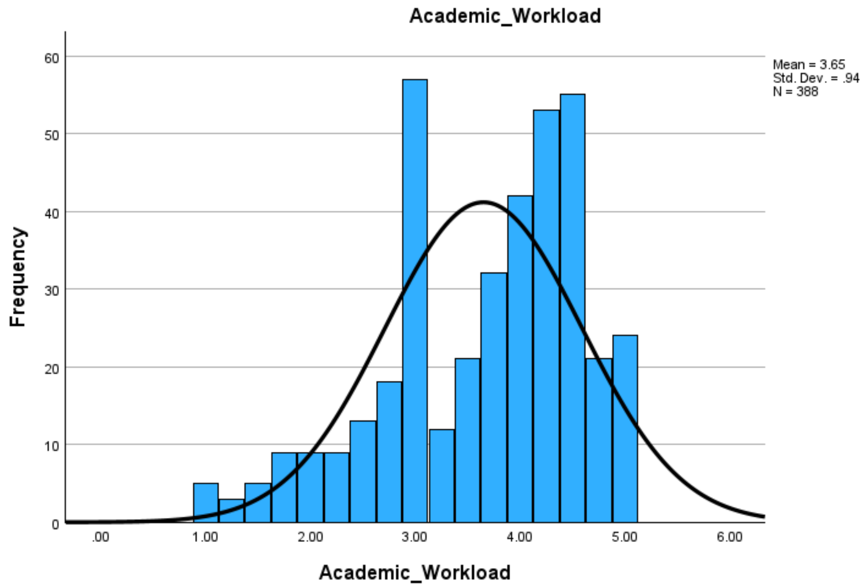
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1.00	3	.8	.8	.8
	1.60	1	.3	.3	1.0
	1.80	2	.5	.5	1.5
	2.00	1	.3	.3	1.8
	2.20	2	.5	.5	2.3
	2.40	3	.8	.8	3.1
	2.60	1	.3	.3	3.4
	2.80	3	.8	.8	4.1
	3.00	24	6.2	6.2	10.3
	3.20	12	3.1	3.1	13.4
	3.40	12	3.1	3.1	16.5
	3.60	18	4.6	4.6	21.1
	3.80	21	5.4	5.4	26.5
	4.00	65	16.8	16.8	43.3
	4.20	28	7.2	7.2	50.5
	4.40	72	18.6	18.6	69.1
	4.60	52	13.4	13.4	82.5
	4.80	23	5.9	5.9	88.4
	5.00	45	11.6	11.6	100.0
	Total	388	100.0	100.0	



IV 4: Academic Workload

Academic_Workload

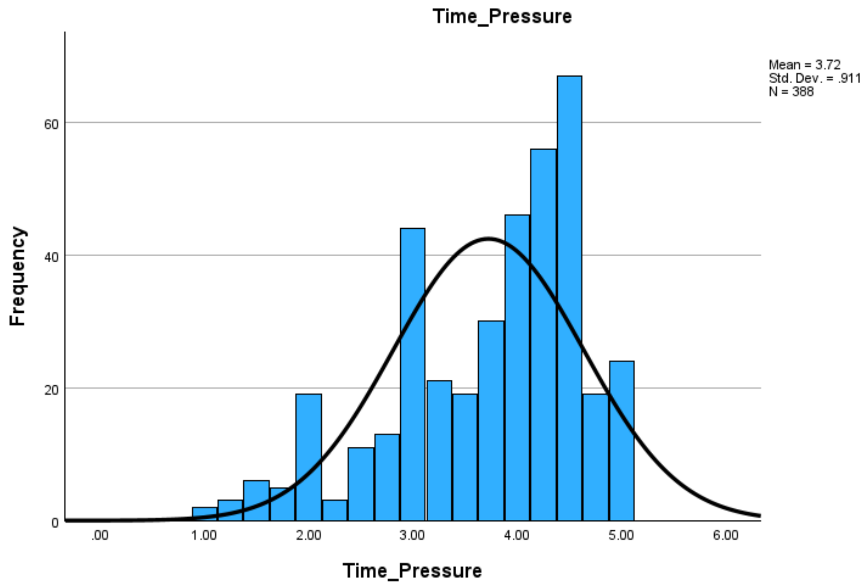
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1.00	5	1.3	1.3	1.3
	1.25	3	.8	.8	2.1
	1.50	5	1.3	1.3	3.4
	1.75	9	2.3	2.3	5.7
	2.00	9	2.3	2.3	8.0
	2.25	9	2.3	2.3	10.3
	2.50	13	3.4	3.4	13.7
	2.75	18	4.6	4.6	18.3
	3.00	57	14.7	14.7	33.0
	3.25	12	3.1	3.1	36.1
	3.50	21	5.4	5.4	41.5
	3.75	32	8.2	8.2	49.7
	4.00	42	10.8	10.8	60.6
	4.25	53	13.7	13.7	74.2
	4.50	55	14.2	14.2	88.4
	4.75	21	5.4	5.4	93.8
	5.00	24	6.2	6.2	100.0
	Total	388	100.0	100.0	



IV 5: Time Pressure

Time_Pressure

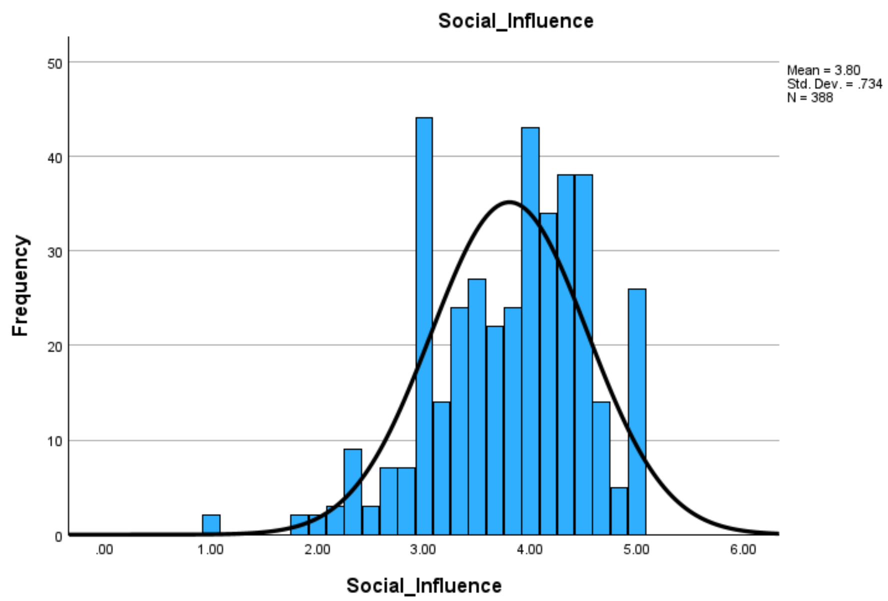
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1.00	2	.5	.5	.5
	1.25	3	.8	.8	1.3
	1.50	6	1.5	1.5	2.8
	1.75	5	1.3	1.3	4.1
	2.00	19	4.9	4.9	9.0
	2.25	3	.8	.8	9.8
	2.50	11	2.8	2.8	12.6
	2.75	13	3.4	3.4	16.0
	3.00	44	11.3	11.3	27.3
	3.25	21	5.4	5.4	32.7
	3.50	19	4.9	4.9	37.6
	3.75	30	7.7	7.7	45.4
	4.00	46	11.9	11.9	57.2
	4.25	56	14.4	14.4	71.6
	4.50	67	17.3	17.3	88.9
	4.75	19	4.9	4.9	93.8
	5.00	24	6.2	6.2	100.0
	Total	388	100.0	100.0	



IV 6: Social Influence

Social_Influence

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1.00	2	.5	.5	.5
	1.83	2	.5	.5	1.0
	2.00	2	.5	.5	1.5
	2.17	3	.8	.8	2.3
	2.33	9	2.3	2.3	4.6
	2.50	3	.8	.8	5.4
	2.67	7	1.8	1.8	7.2
	2.83	7	1.8	1.8	9.0
	3.00	44	11.3	11.3	20.4
	3.17	14	3.6	3.6	24.0
	3.33	24	6.2	6.2	30.2
	3.50	27	7.0	7.0	37.1
	3.67	22	5.7	5.7	42.8
	3.83	24	6.2	6.2	49.0
	4.00	43	11.1	11.1	60.1
	4.17	34	8.8	8.8	68.8
	4.33	38	9.8	9.8	78.6
	4.50	38	9.8	9.8	88.4
	4.67	14	3.6	3.6	92.0
	4.83	5	1.3	1.3	93.3
	5.00	26	6.7	6.7	100.0
	Total	388	100.0	100.0	



Appendix I

Pearson Correlation Coefficient

Correlation between Academic Self-Efficacy with AI Dependency

Correlations

		AI_Dependency	Academic_Self_Efficacy
AI_Dependency	Pearson Correlation	1	.006
	Sig. (2-tailed)		.901
	N	388	388
Academic_Self_Efficacy	Pearson Correlation	.006	1
	Sig. (2-tailed)	.901	
	N	388	388

Correlation between Academic Stress with AI Dependency

Correlations

		AI_Dependency	Academic_Stress
AI_Dependency	Pearson Correlation	1	.607***
	Sig. (2-tailed)		<.001
	N	388	388
Academic_Stress	Pearson Correlation	.607***	1
	Sig. (2-tailed)	<.001	
	N	388	388

***. Correlation at 0.001(2-tailed)

Correlation between Performance Expectancy with AI Dependency

Correlations

		AI_Dependency	Performance_Expectancy
AI_Dependency	Pearson Correlation	1	.483***
	Sig. (2-tailed)		<.001
	N	388	388
Performance_Expectancy	Pearson Correlation	.483***	1
	Sig. (2-tailed)	<.001	
	N	388	388

***. Correlation at 0.001(2-tailed)

Correlation between Academic Workload with AI Dependency

Correlations

		AI_Dependency	Academic_Workload
AI_Dependency	Pearson Correlation	1	.684***
	Sig. (2-tailed)		<.001
	N	388	388
Academic_Workload	Pearson Correlation	.684***	1
	Sig. (2-tailed)	<.001	
	N	388	388

***. Correlation at 0.001(2-tailed)

Correlation between Time Pressure with AI Dependency

Correlations

		AI_Dependency	Time_Pressure
AI_Dependency	Pearson Correlation	1	.660***
	Sig. (2-tailed)		<.001
	N	388	388
Time_Pressure	Pearson Correlation	.660***	1
	Sig. (2-tailed)	<.001	
	N	388	388

***. Correlation at 0.001(2-tailed)

Correlation between Social Influence with AI Dependency

Correlations

		AI_Dependency	Social_Influence
AI_Dependency	Pearson Correlation	1	.545***
	Sig. (2-tailed)		<.001
	N	388	388
Social_Influence	Pearson Correlation	.545***	1
	Sig. (2-tailed)	<.001	
	N	388	388

***. Correlation at 0.001(2-tailed)

Appendix J

Multiple Linear Regression Analysis

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Social_Influence, Academic_Self_Efficacy, Performance_Expectancy, Academic_Workload, Academic_Stress, Time_Pressure[b]	.	Enter

a. Dependent Variable: AI_Dependency

b. All requested variables entered.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.734[a]	.539	.532	.65199

a. Predictors: (Constant), Social_Influence, Academic_Self_Efficacy, Performance_Expectancy, Academic_Workload, Academic_Stress, Time_Pressure

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	189.308	6	31.551	74.222	<.001[b]
	Residual	161.961	381	.425		
	Total	351.269	387			

a. Dependent Variable: AI_Dependency

b. Predictors: (Constant), Social_Influence, Academic_Self_Efficacy, Performance_Expectancy, Academic_Workload, Academic_Stress, Time_Pressure

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	.208	.233		.891	.374		
	Academic_Self_Efficacy	-.113	.041	-.102	-2.758	.006	.891	1.123
	Academic_Stress	.129	.067	.109	1.935	.054	.381	2.626
	Performance_Expectancy	.150	.062	.111	2.435	.015	.583	1.714
	Academic_Workload	.365	.064	.360	5.736	<.001	.307	3.254
	Time_Pressure	.148	.070	.142	2.119	.035	.271	3.691
	Social_Influence	.191	.063	.147	3.020	.003	.509	1.965

a. Dependent Variable: AI_Dependency

Collinearity Diagnostics[a]

Model	Dimension	Eigenvalue	Condition Index	Variance Proportions						
				(Constant)	Academic_Self_Efficacy	Academic_Stress	Performance_Expectancy	Academic_Workload	Time_Pressure	Social_Influence
1	1	6.848	1.000	.00	.00	.00	.00	.00	.00	.00
	2	.074	9.624	.02	.37	.01	.00	.04	.03	.00
	3	.026	16.215	.20	.51	.01	.13	.16	.02	.01
	4	.016	20.389	.02	.02	.19	.03	.02	.01	.81
	5	.014	22.179	.74	.04	.17	.24	.11	.02	.04
	6	.012	24.231	.02	.01	.56	.59	.22	.00	.04
	7	.010	25.587	.00	.05	.07	.01	.45	.92	.11

a. Dependent Variable: AI_Dependency