THE INTERRELATIONS BETWEEN ARTIFICIAL INTELLIGENCE (AI) USAGE AND ACADEMIC PERFORMANCE

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BY

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DECLARATION

I hereby declare that:

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

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

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

(4) The word count of this research report is 10862 .

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LIST OF ABBREVIATIONS

AAC	Academic Performance
AI	Artificial Intelligence
CAGR	Compound Annual Growth Rate
CHAT-GPT	Chat Generative Pre-training Transformer
EFT	Efficient Use
ETD	Extended Use
GPA	Grade Point Average
HEI	Higher Education Institution
IAU	International Association of Universities
ICE	Intention to Continue Exploring
ICT	Information and Communications Technology
INE	Innovative Use
IS	Information System
IT	Information Technology
NLP	Natural Language Processing
PLS-SEM	Partial Least Squares Structural Equation Modelling
RGR	Regular Use
RID	Reinformed Use
RUE	Routine Use
SDT	Self Determination Theory
WHED	World Higher Education Database

PREFACE

The incredible developments in artificial intelligence (AI) have impacted a number of sectors, including education, where AI are becoming more prevalent for improving learning and enhancing academic outcomes. My interest in this area of study came from a desire to better understand how these technologies affect students' academic performance. In an era where AI could offer personalised learning, accelerate study processes, and even assist in academic tasks, I was interested on the implications of using it on student performance.

With the support of my supervisor, we narrowed down the scope of the research to examine the interrelations between various types of AI usage and their impact on academic performance. While numerous research efforts have examined into the impact of technology on education, there were limited research that addressed the various ways in which AI might affect academic performance. It therefore stressed the significance of carrying out research that would offer a more comprehensive view of how different usages of AI influences educational performance.

I hope that our work assists in filling the gap in the field and encourage further studies on the various uses of AI in the educational sector.

ABSTRACT

With the increasing prevalence of integrating Artificial Intelligence (AI) into the education sector, educators and administrators are positioned to be equipped with an extensive grasp of the possibilities for AI in education. Previous studies have mostly concentrated on technology tools, algorithms, validation, and utilisation rather than their impact on student performance. As such, the focus on learning outcomes tends to remain limited. This paper intends to bridge the gap by studying how different types and extents of the use of AI may affect how students do in school, especially within higher education institutions. Six different uses of AI, routine use, regular use, efficient use, extended use, innovative use and reinformed use, were selected to look into their effect on students' academic performance. A survey was designed and distributed to higher education students. Partial least square structural equation modelling (PLS-SEM) was adopted for studying the associations between the six AI usages and students' academic performance. The results suggested that four of the six constructs were the primary drivers of academic achievement. In accordance with the PLSpredict analysis, the research model nevertheless retained predictive potential in representing the findings that were observed. The outcomes of this paper offered useful insights for academicians and practioners to improve the incorporation of AI in education strategically, while also setting a sturdy foundation for further investigation into the impact of using AI on academic performance.

Keywords: Artificial Intelligence, AI usages, Academic Performance, AI in education, PLS-SEM

CHAPTER 1: RESEARCH OVERVIEW

1.0 Introduction

The opening chapter presents the paper's introduction, beginning with the study's setting, moving on to the research gap, which leads to the establishment of questions and objectives of this research, and concluding with the vitality of carrying out the research.

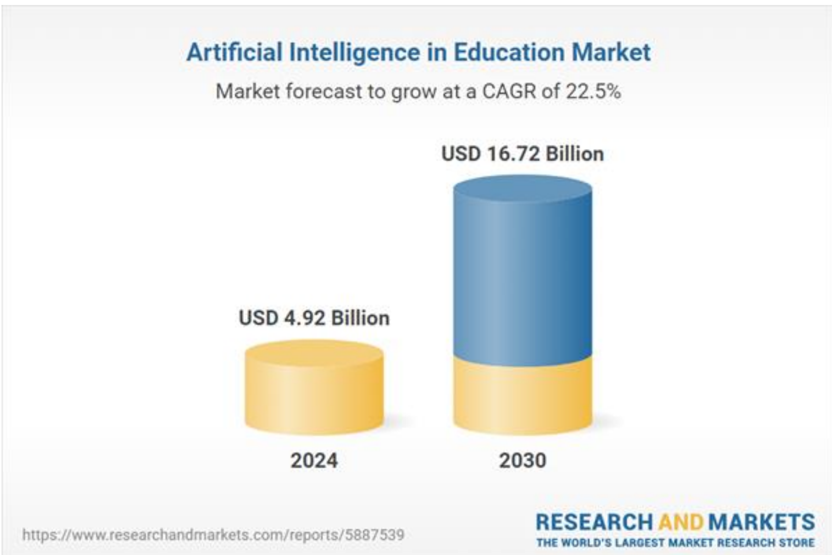
1.1 Research Background

Artificial Intelligence (AI) has increasingly being adopted in numerous major industries, including education. AI forms an inevitable part of education and has a considerable impact on education. The private industry is continuously establishing 'intelligent', 'adaptive' and 'personalised' educational technologies for adoption in educational institutions worldwide (Miao et al., 2021). Educators and administrators are anticipated to have a thorough understanding of AI's possibilities in education to incorporate this revolutionary technology into education practice (Holmes & Tuomi, 2022). Rather than merely automating the learning and educating approach, AI contributes to opening up educational possibilities that would have been otherwise challenging to attain, including fostering peer learning, AI-driven student evaluation, continuous examination, AI studying partners for pupils, and AI instructional helpers for educators, and serving as an instrument for research that advances the field of education (Holmes et al., 2023).

The AI in the global education sector has risen substantially in recent years. With a compound annual growth rate (CAGR) of 22.54%, it is anticipated to increase from

$4.03 billion in 2023 to $4.92 billion in 2024, and $16.72 billion by 2030 (The Business Research Company, 2024). The widespread utilisation of online educational services, programmes advocating personalised learning, the establishment of flexible educational platforms, the deployment of analytics and big data for learning, and AI tutoring platforms adoptions are all factors contributing to advancing and expanding AI applications in education (The Business Research Company, 2024). In Malaysia, the government has initiated a number of programmes within the national policy regarding science, technology, and innovation, highlighting the purporse of AI in promoting economic growth and academic achievement. To exemplify, 'AI Untuk Rakyat' and 'AI Talent Roadmap for Malaysia 2024-2030' are among the initiatives proposed by the government (Bernama, 2024). These initiatives are meant not just to incorporate AI technologies into schools, but also to prepare pupils with the critical skills required to thrive in a digital economy. In Malaysia's educational system, AI is implemented in a variety of ways. From elementary to higher education, AI technologies are utilised to offer personalised educational experiences in which software caters to each student's learning needs and preferences (Sharif Study, 2024).

Figure 1.1 Market Forecast of AI in Education Market



Source: The Business Research Company. (2024). *AI in Education Global Market Report 2024*. https://www.researchandmarkets.com/report/education-ai

1.2 Research Problem

The existing usage of AI in the setting of higher education remains in the initial phase, primarily owing to an absence of interest from higher education institutions. The vast majority of current AI applications for educational use concentrate mainly on content presentation and comprehension assessment (Bates et al., 2020). Published papers regarding AI in educational contexts are developed by computer scientists, who employ learning models based on how computers or networks of computers function. They appear to be more concerned with the instruments, algorithms, and validation and use than with their influence on the outcomes of learning. While they suggest a certain degree of enthusiasm for educational results, it is primarily to validate the algorithms. As a result, the emphasis on learning outcomes is often shallow. Priority is placed on matters that are easily quantifiable, including short-term memory assessments or dropout rates among students (Zawacki-Richter et al., 2019).

AI has introduced novel approaches for boosting learning and educating in higher learnin. Nonetheless, there is relatively limited esearch centred around the roles, impacts, and implications of using AI in higher education. Furthermore, it is unknown how algorithms based on AI are commonly utilised and how they affect higher education (Ouyang et al., 2022). Much research have been conducted focusing on the opportunities as well as challenges of AI in higher learning (Zawacki-Richter et al., 2019; Bates et al., 2020; Kuleto et al., 2021). Yet, there are limited papers regarding the outcomes of using AI on the educational performance of university pupils. Among the limited research on AI usage, nearly half of the studies were undertaken in specific fields such as language learning, engineering, and computer science. Furthermore, nearly all of the study was carried out only at the undergraduate level (Crompton & Bruke, 2023). Hence, to acquire a thorough comprehension of AI's influences on academic achievement, it is essential to study its use across higher education institutions instead of concentrating solely on specific departments or educational levels. The rapid dissemination of AI in the educational industry prompts the question of how the variety and degree of use of AI could possibly affect students' academic performance, particularly those in HEIs.

There is a critical need to evaluate its actual impact on educational performance.

1.3 Research Questions & Research Objectives

Following the research background, below is the research questions and objectives developed.

1.3.1 Research Questions

Research questions are established to explore the interrelation between various independent variables of AI usage and the dependent variable, the academic performance of higher education institution students.

The subsequent six are the research questions to be addressed:

1. Is there a positive connection between routine use of AI and the academic performance of higher education institution students?
2. Is there a positive connection between regular use of AI and the academic performance of higher education institution students?
3. Is there a positive connection between efficient use of AI and the academic performance of higher education institution students?
4. Is there a positive connection between extended use of AI and the academic performance of higher education institution students?
5. Is there a positive connection between innovative use of AI and the academic performance of higher education institution students?
6. Is there a positive connection between reinformed use of AI and the academic performance of higher education institution students?

1.3.2 Research Objectives

The puporses of this research are to explore the interrelations between independent and dependent variables, with the primary aim of uncovering whether the different AI usage impact the academic performance of higher education institution students.

The following six are the research objectives to be achieved:

1. To discover whether there is a positive connection between routine use of AI and the academic performance of higher education institution students.
2. To discover whether there is a positive connection between regular use of AI and the academic performance of higher education institution students.
3. To discover whether there is a positive connection between efficient use of AI and the academic performance of higher education institution students.
4. To discover whether there is a positive connection between extended use of AI and the academic performance of higher education institution students.
5. To discover whether there is a positive connection between innovative use of AI and the academic performance of higher education institution students.
6. To discover whether there is a positive connection between reinformed use of AI and the academic performance of higher education institution students.

1.4 Research Significance

Research that studies the interrelations between various usage of AI and the educational performance of higher education institution students can provide insights and recommendations to practitioners and academicians, enabling effective policy development, educational strategy formulation, and resource allocation. It is critical to address the matter of integrating AI into higher education (Neumann et al., 2023). Some educators are debating whether to embrace or forbid AI in their courses. It has thus prompted demands for more stringent rules and measures for educational misconduct using AI (Chan, 2023). Understanding how students utilise AI can enable the formation of policies that promote and encourage effective and ethical use of AI in higher education. There are also growing concerns regarding efforts to foster the use of AI in higher educational institutions in improving students' educational performance (Wang et al., 2021). AI has profoundly influenced educational management, educational innovation, and educational behaviour (Nelson et al., 2019). Moreover, higher education institutions should draw and retain students and educators by providing adequate technological resources. The lack of digital and technological educational resources due to institutions' inability to invest could hinder students' potential, leading them to lag behind others in terms of digital literacy (Hannan & Liu, 2023). Thus, studying the interrelations between multiple AI usage and educational outcomes facilitates proper allocation of resources, which is critical for enhancing operational effectiveness and enhancing student achievement.

1.5 Chapter Summary

Chapter 1 served as an introduction to the research topic that studies the interrelation between AI usage and academic outcomes. The study background emphasised the growing cruciality of AI in education. The problem statement acknowledged the gap in how different types of AI usage influence the academic performance of HEI's students. Research questions and objectives were constructed, acting as a guidance for the study. The chapter ended by stressing the significance of conducting such research.

CHAPTER 2: LITERATURE REVIEW

2.0 Introduction

The second section discusses the underlying theory and constructs that serve as the foundation of the study. It begins by outlining how the underlying theory will be applied to support the study. The dependent variable, academic performance, will then be introduced, followed by six independent variables i.e. routine use, regular use, efficient use, extended use, innovative use and reinformed use. The conceptual framework will then be developed, followed by a discussion of the hypotheses that have been developed.

2.1 Underlying Theory

2.1.1 Self-Determination Theory

Self Determination Theory (SDT), supported by extensive research, is a widely recognised theory of human drive and psychological well-being (Ryan & Deci, 2017). Serving as an approach that addresses the motivating elements of personality and interpersonal conduct, it studies the relationship between fundamental psychological needs and well-being, mental prospering and standard of life. SDT is a framework that addresses the elements which encourage or compromise self-motivation, independent external drive, and mental well-being, all of which are particularly applicable in educational contexts (Ryan & Deci, 2020). It has long been used to examine and predict students' academic performance. SDT has been concentrating on multiple forms of motivation which vary from autonomous to regulated in order to determine outcomes including performance, involvement, power, and psychological well-being (Ryan & Deci, 2022).

The term "need" indicates a want or desire. It additionally implies what is deemed critical or indispensable for a person's physical well-being and effective functioning. From the context of psychology, the feeling of satisfaction is essential for an ideal healthy functioning throughout individuals and society. SDT proposes three fundamental psychological needs, involving independence, connection, and competence (Chen et al., 2015). Independence implies the level to which one feels self-determined, well-prepared, and motivated while engaging in an activity; connection is defined as the degree to which one feels intimate and truly connected with others; and competence implies feeling capable and effective of attaining the intended results (Ryan, 1995). Meeting all of these psychological demands has been considered to be commonly required for ensuring individual development (Chen et al., 2015).

Fulfilling fundamental psychological desires and independent drive is often associated with favourable behavioural outcomes and perceptions of performance (Lourenco et al., 2022). Hence, SDT serves as a foundation that governs the study. In this research, the academic performance of students is based on their perceived competence in their studies. It refers to the experience of proficiency, the belief that one is able to thrive and improve (Ryan & Deci, 2020). The desire for competence is most effectively fulfilled in organised settings that provide adequate challenges, constructive criticism, and room for improvement (Ryan & Deci, 2020). Moreover, a student's different uses of AI are determined by themselves. In other words, the various types of AI usage are based on student's perception of their usage of AI.

2.2 Review of Variables

2.2.1 Dependent Variable: Academic Performance

Zawacki-Richter et al. (2019) asserted that AI-powered services and technologies could benefit students, educators, and administrators across the student learning lifecycle. AI usage under the setting of education is vital as it has the potential to drastically enhance processes of instruction and learning while also encouraging knowledge building. As technological development continues, AI will eventually advance to smart learning and education (Zhao & Liu, 2019). It has emerged as a significant technology influencing societal and educational development, and it has become essential to examine AI's potential to improve students' creativity and academic achievement (Wang et al., 2022). Thus, examining the different usage of AI influences on academic performance is critical.

Student academic performance serves as one of the most significant components of any educational institution (Jokhan et al., 2018). A number of research (Rashid & Asghar, 2016; Alshater, 2022; Wecks et al., 2024) have been done on the connections between the usage of technology and educational performance. Rashid and Asghar (2016) stated that there was an adverse yet negligible correlation between the average technology use and students' academic outcomes. The rationales for this encompass that, while students are exposed to various types of technology, they may not be optimising their technological abilities for educational purposes, and excessive frequency usage and multitasking could end up in distractions, leading to limited time for academic assignments (Rashid & Asghar, 2016). Alshater (2022) examined the potential uses of artificial intelligence, specifically natural language processing (NLP), in improving academic achievement, with economics and finance as a starting point. His studies have shown that the use of AI has the possibility of profoundly improving academic performance in general, and particularly in economics and finance. Wecks et al. (2024) revealed that using Generative AI detrimentally impact students' test performance. Positive functions including simplifying information, boosting learning incentives, or offering simple answers, might still exist, but they are eventually outweighed by the adverse impacts. They additionally highlighted that while AI would seem to facilitate easier studying, it could have the opposite effect on academic achievements.

In this paper, academic performance is examined by the students' latest CGPA as well as their perceived competency. The use of AI has been proven to have an influence on academic performance. Nonetheless, the question of whether academic performance will be positively influenced by the various uses of AI is yet to be determined. Routine use, regular use, efficient use, extended use, innovative use and reinformed use of AI will be examined to identify their impact on academic performance.

2.2.2 Independent Variable: Routine Use

Individual performance may fluctuate as a result of variations regarding the way AI solutions are used (Sun et al., 2019). Routinisation describes the incorporation of modern technologies into daily activities and operations; nonetheless, it does not imply that an individual takes full advantage of the system's capabilities (Sundaram et al., 2007). It signifies the degree to which a technology feature is being tailored into and utilised as an embedded and consistent aspect of a person's daily routine, although it does not automatically imply that an individual is using the technology's full functionality (Chen et al., 2020).

Routine use indicates the level to which AI is being used constantly in a systematic way (Hu & Pan, 2023). It refers to individuals who use information systems on a routine basis to assist with their everyday tasks (Li et al., 2013). Using AI routinely necessitates task execution on a regular basis, hence the capacity of AI to carry out routine activities efficiently is critical

(Hu & Pan, 2023). To use technology routinely, an individual has to initially be interested in using the technology, and then actually utilise it. Growing utilisation offers a chance for technology to be infused and routinised. In principle, the more an individual interacts with technology, the more prone he or she is to embrace it and, as a result, use it to enhance efficiency and productivity (Sundaram et al., 2007). Routine IT use stems from rational choice-making and purposeful objectives. Emotion, along with cognition, may influence the decision to continue using or the establishment of a desire to do so. In predictable circumstances, routine IT use can become habitual, resulting in proficient behaviours being carried out unintentionally (De Guinea & Marcus, 2009). The educational technology sector is continuously bombarding educators with innovative technologies that are routinely used in the educational setting. Routine use of educational technologies occurs when students are familiar with the technology and have no intention to change it (Bourrie et al., 2016).

2.2.3 Independent Variable: Regular Use

Regular use defines the degree where an individual uses technology (Sundaram et al., 2007). It can be explained as the consistent use of a particular technology over an extended period (De Guinea & Markus, 2009). It describes the repetitive use of information systems with predictable patterns of behaviour (Pan et al., 2017). Regularity outlines a specific behavioural habit that is established and consistent (Limayem et al., 2007). Ma et al. (2014) provided preliminary proof stating that regular use, also known as consistency in information technology use, significantly enhances repetitive behaviour. It particularly raises the effect of present behaviour on forthcoming behaviour, implying that it is supportive of establishing a regular behavioural practice more thoroughly. Regular engagement with technology can develop sentiments of social proximity, emphasising the adaptability of characteristics acquired through relationships with others. It suggests that consistent engagement with technology, in addition to terms of length and frequency, can build a social attachment to technology (Christoforakos et al., 2021).

According to Larsen et al. (2009), utilisation is both the extent and regularity with which functions are used. It is suggested by the authors that users' contentment with the actual IS has evolved regardless of their regularity of use. Nevertheless, it does not imply that contentment is not determined by using the system. It is speculated that satisfaction may be dependent on the overall usage experience. This suggests that a general perspective develops independently and is unrelated to the regularity of use. The satisfaction of technology has a great impact on the educational achievement, and functional competence of students (Memon et al., 2022).

2.2.4 Independent Variable: Efficient Use

To fully capitalise on information systems, they ought to be used efficiently and effectively (Burton-Jones & Grange, 2013). System usage is characterised as a user, system, and task, with a task representing a goal-driven action (Burton-Jones & Straub, 2006). Making efficient use of information systems is described as using a system in a manner that facilitates one to achieve one's objectives. The focus moves from utilising the system to accomplish an objective-directed task to utilising it to assist in achieving a particular objective (Burton-Jones & Grange, 2013). Pan et al. (2017) described efficient use as an information system that appears efficient at executing specified activities. Efficient use may be comparable to the idea of perceived usefulness or performance expectancy, a construct suggested by Venkatesh et al. (2003), which is described as a stage where a user believes that utilising a system would lead to enhancement of their work effectiveness. Yet, the concepts vary in terms of scope as efficient use concentrates on the positive outcomes that result from use rather than merely how it is utilised. In addition, they vary when it comes to raters, with perceived usefulness referencing a user's anticipation or perspective, while efficient use is objectively evaluated (Burton-Jones & Grange, 2013).

According to Kalirajan (1991), technological advancements and efficient technology use can impact performance. Efficient technology use or technical efficiency can be described as having the capacity of maximising output with a particular amount of standard resources and technology, irrespective of demand from the sector. The usage of information technology which fosters productive and efficient action is advantageous to individuals as well as corporations (De Guinea & Markus, 2009). Educational administrators, educators, and pupils are conscious of the tendency whereby technology use in educational institutions will alter future individuals' effectiveness and efficiency when using various types of technology (Tang & Austin, 2009).

2.2.5 Independent Variable: Extended Use

The term "extended use" suggests the action of using additional technological functions to assist a user in executing their tasks. Extended use highlights the many aspects that comprise individual information system use during the initial phase of implementing the system. It describes the level to which system features are utilised optimally (Wang & Hsieh, 2006). Extended use is how individuals make use of additional technology's functions and features to deal with a more thorough scope of activities and responsibilities (Saga & Zmud, 1994, as cited in Wang & Hsieh, 2006). Schwarz (2003, as cited in Wang & Hsieh, 2006) introduced deep usage, a concept similar to extended use, implying the degree to which certain technological functions are used. As claimed by Wang and Hsieh (2006), individuals have the potential to get more knowledge and appreciation about a system by using the technology in an extended way. Such an increased level of expertise and comprehension allows individuals to use the technology in novel ways.

When users are exposed to a new technology, they often have difficulty figuring out ways to employ it to perform their tasks. They will initially utilise only a few technology features; nevertheless, they will eventually discover other beneficial functions (Robey et al., 2002). At the point when users first adopt the information system, they enjoy merely a simplified and rudimentary experience. Upon accumulating additional experience, they ultimately move forward to the regular phase, where the use of the system is no longer considered unusual or novel (Saga & Zmud, 1994 as cited in Hsieh & Wang, 2007). As users grow more accustomed to the system, they may become unsatisfied with their present use condition and therefore seek additional functions that can complement their work (Hsieh & Wang, 2007). Extended use develops following routine use (Saga & Zmud, 1994 as cited in Hsieh & Wang, 2007). According to Sun (2012), when confronted with triggers, such as an unfamiliar assignment, individuals may deliberately reflect on and then adjust the system they use. These modifications enable them to make use of and extend the capacities of an information system, hence improving their productivity and performance (Tyre & Orlikowski, 1994; Jasperson et al., 2005).

2.2.6 Independent Variable: Innovative Use

Innovative use demonstrates the point at which individuals probe into an information system and uncover new features (Pan et al., 2017). To use technology innovatively, individuals must first develop consistent utilisation, before exploring and discovering novel ways to use the technology (Wang et al., 2008). Ciborra (1992) claimed that innovating with technology is an essential step towards achieving innovation success. Individuals who seek to innovate could discover effective technological solutions that can enhance performance (Ahuja & Thatcher, 2005). During the infusion phase, when technology applications are deeply integrated into the individual's working procedures, they will seek to innovate with the technology to satisfy current but unfulfilled task requirements and apply them to new demands of work (Saga & Zmud, 1994, as cited in Ahuja & Thatcher, 2005).

Personal innovativeness, or a willingness to make changes, is a key factor in inventive behaviour (Hurt et al., 1977). Certain individuals tend to be more tolerant of change and ready to experiment with new things than other individuals (Midgley & Dowling, 1978). A dynamic information system comprises several minor advances, which are more likely to be appreciated by innovative individuals (Thong et al., 2006). They will be more adaptable to the evolving nature of dynamic information systems, thereby increasing their eagerness to use the systems (Hong et al., 2011). Individuals with a higher degree of creativeness are often more prone to explore innovative features as they demonstrate their curiosity and openness to new experiences (Hong et al., 2011). Innovative use of technology can provide significant advantages and value to organisations (Gupta & Karahanna, 2004). Individuals are able to gain from breakthrough technological applications through innovative use. Organisations, including educational institutions, invest millions in sophisticated technology, yet only a portion of its potential is exploited. Thus, encouraging individuals to discover innovative and creative uses for such technologies is critical to maximising their return on investment (Gupta & Karahanna, 2004).

2.2.7 Independent Variable: Reinformed Use

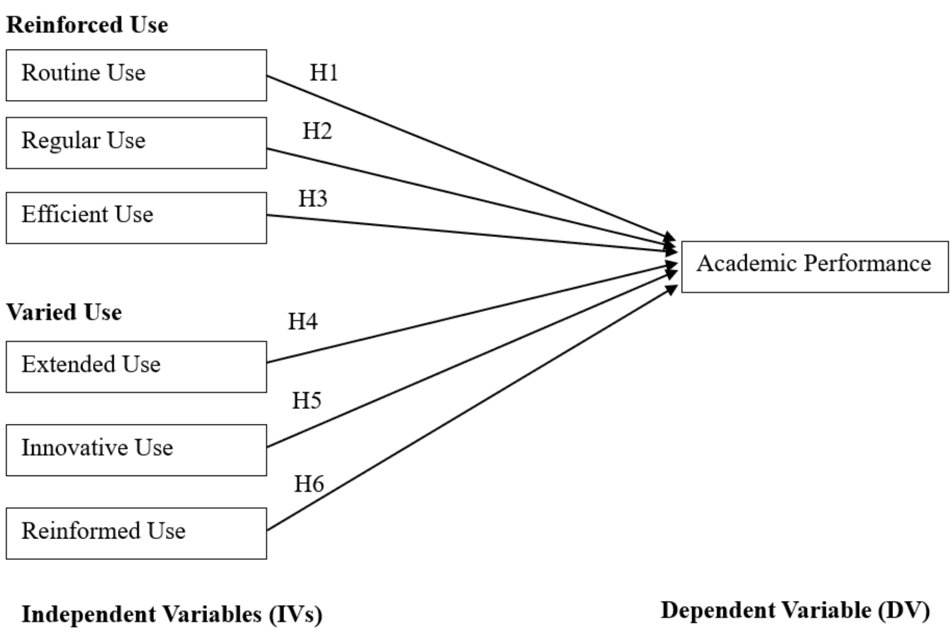
Reinformed use is known as the intention to continue exploring (ICE). Continuous usage of an information system represents patterns of behaviour that demonstrate the sustained use of a certain system. It is a type of post-adoption action (Limayem et al., 2007). From the individual level, the continual using of technology describes the point at which technology use exceeds conscious acts and becomes an essential component of typical daily activities (Bhattacherjee, 2001). Such behaviour is prone to rely on a more habitualised (autonomous) nature (Limayem et al., 2007).

An intention is a cognition that influences the behaviour of an individual (Venkatesh et al. 2006). Intention to explore technology, or in other words, the plan to learn more about a technology, is an indicator of a user's tendency to be creative in information technology that represents an individual's commitment and motivation to learn about an emerging technology and uncover its hidden features (Nambisan et al., 1999). The intention to continue exploring, on the flip side, suggests a user willingness to explore a system for future work uses continuously (Maruping & Magni, 2015). It reflects an individual developing an intention and goal internally to interact with the technology as it develops (Maruping & Magni, 2015). Intentions often concentrate on the fundamental concepts and motives that influence behaviour (Venkatesh et al. 2006). The beliefs regarding how modern technology could impact an individual's ability to accomplish his or her tasks advantageously influenced the willingness of users to explore further (Magni et al., 2010). Intentions play an essential role in shaping behaviour among users (Davis et al., 1989; Venkatesh et al., 2003; Venkatesh et al., 2006; Venkatesh et al., 2008). There is an association between intentions and behaviours, which involves technology usage (Venkatesh et al. 2003; Venkatesh et al. 2008). The intention to continue exploring emphasises an individual's interests and willingness to continue looking into a particular technology for more effective use (Maruping & Magni, 2015).

2.3 Proposed Conceptual Framework

To study the interrelations between AI usage and the academic performance of higher education institution students, a conceptual framework is developed, consisting of six independent variables leading to one dependent variable. The first three independent variables, including routine use, regular use and efficient use, are categorised under the concept of reinforced use. The following three independent variables, involving extended use, innovative use and reinformed use, are categorised under the concept of varied use. The educational performance of pupils in higher education institution constitutes the dependent variable.

Figure 2.1 Conceptual Framework of the Research



Source: Developed for the research.

The conceptual framework, displayed in Figure 2.1, depicts the proposed relationships between the six different usages of AI and the academic performance of higher education institution students. The Self-Determination Theory is used to support the framework, investigating how students perceived their academic performance through different uses of AI.

2.4 Hypotheses Development

The relationships between variables are examined by establishing hypotheses as follows:

2.4.1 Routine Use and Academic Performance

Librenjak et al. (2016) discovered that routine utilisation of e-learning enhances students' language proficiency. Constant e-material students improved by an average of 20.3% after every semester of study, whereas non-consistent users progressed by just 11.6%. Beatson et al. (2020) discovered that active application of Quitch (a game-based technology) among business students in Accounting and Management courses improves their academic success. The consistent usage of Quitch allowed students to be fully involved with the educational activities throughout the semester, thereby enhancing their academic performance. According to Prieto-Latorre et al. (2022), using the Internet (excluding social networking sites) has a positive association with better academic achievement. They discovered that students who make use of the Internet routinely as an educational resource or periodically for academic purposes have better learning outcomes. Thus, the following hypothesis is established:

H1: There is a positive association between the routine use of AI and the academic performance of higher education institution students.

2.4.2 Regular Use and Academic Performance

Wentworth and Middleton (2014) examined the association amongstudents' regular usage of technology and their educational achievement as evaluated by GPA, SAT scores, time spent studying, and prospective course performance. Their hypotheses were partly supported, with the regularity of using technology having an adverse association with academic performance. Regular usage of interactive technology could improve students' academic performance while excessive use of technology, in particular for entertainment, could negatively impact students' academic achievement (Anthony et al., 2021). According to Gromada (2019 as cited in Anthony et al., 2021), using interactive technology for more than 2 hours per day has an adverse impact on students' academic performance, whereas moderate usage positively influenced learning outcomes. Sanders et al. (2019) indicated that using technology for education led to better academic outcomes. Thus, the subsequent hypothesis is constructed:

H2: There is a positive association between the regular use of AI and the academic performance of higher education institution students.

2.4.3 Efficient Use and Academic Performance

Olelewe et al. (2019) discovered that using technology efficiently in blended educational efforts, especially gamification, can improve student retention as well as engagement. Navarro-Martinez and Peña-Acuña (2022) asserted that the influence of technology usage on academic performance is not necessarily detrimental. When used effectively and efficiently, it can lead to good academic achievements and a favourable effect on the development of students. Ishaq et al. (2020) discovered that productive use of technology has a considerable favourable effect on students. A large number of students stated that they used technology productively to complete various tasks. Efficient technology use enhances students' abilities and skills, which can be highly beneficial. Furthermore, the efficient incorporation of ICT into classroom activities enhances student engagement, motivation, and enthusiasm, enabling students to absorb knowledge more effectively while also enhancing their retention and comprehension (Ishaq et al., 2020). Thus, the subsequent hypothesis is proposed:

H3: There is a positive association between the efficient use of AI and the academic performance of higher education institution students.

2.4.4 Extended Use and Academic Performance

Yueng et al. (2021) findings suggested that technology is neither advantageous nor detrimental to educational outcomes when used primarily for the intent to deliver content (such as information displayed on a computer monitor versus on print), yet it can be advantageous when it incorporates distinctive characteristics employing appropriate educational concepts. Ahmed et al. (2020) revealed that using various types of technology features has a considerable impact on students' learning outcomes. Their results indicated that technological features strengthen university students' performance in school. Alshater (2022) claimed that the extended use of ChatGPT (a Generative AI) to advance academic performance. Comprehensive usage of ChatGPT and other AI techniques could assist academicians to better analysing and interpreting vast volumes of data, developing realistic circumstances for evaluating and testing theories, and effectively conveying their results in an easily understood way. The use of these features has the capacity to significantly improve (Alshater, 2022). Hence, the subsequent hypothesis is constructed:

H4: There is a positive association between the extended use of AI and the academic performance of higher education institution students.

2.4.5 Innovative Use and Academic Performance

Rashid and Asghar (2016) discovered that Using technology had a minimal direct correlation with school performance. They concluded that using technology has a detrimental, although small, impact on academic attainment;

nevertheless, significant positive associations have been observed between particular kinds of technology, including social media use. This proved that employing technology innovatively can influence academic performance. Çakıroğlu et al. (2017) findings showed that using a combination of features has a advantageous incentive impact on engagement. Furthermore, the widespread utilisation of gamification elements has secondary effects on educational achievement since they enhanced student engagement. The findings of Youssef et al. (2022) showed that interactive, creative and innovative use of technology increases the likelihood of students obtaining higher grades. The performance of students is enhanced when an educational institution employs supportive and creative instructional approaches that involve the inventive use of ICTs. Thus, the following hypothesis is established:

H5: There is a positive association between the innovative use of AI and the academic performance of higher education institution students.

2.4.6 Reinformed Use and Academic Performance

Park and Weng's (2020) studies demonstrated that students' academic results improve when they possess independency as well as intention in making good adoption of technology. In other words, students' interest in technology had a strong positive correlation with academic accomplishment. This can be due to the reason that pupils who are keener on technology are more inclined to participate in educational projects involving technology or the Internet. Furthermore, such students would be more enthusiastic and excited about learning through technology (Park & Weng, 2020). Based on Gómez-Fernández and Mediavilla (2021), students who are more interested in exploring technology continuously accomplish better in science, mathematics, and language. Moreover, a more significant positive relationship between students' interest in exploring technology and educational outcomes has been explored among the lowest-performing pupils (Gómez-Fernández &

Mediavilla, 2021). Thus, the subsequent hypothesis is created:

H6: There is a positive association between the reinformed use of AI and the academic performance of higher education institution students.

2.5 Chapter Summary

Chapter 2 commenced by conducting a review of the theory and variables of the study. It outlined the proposed conceptual framework as a base to analyse the interrelations between six different usages of AI and academic performance. Hypotheses were then constructed to be tested in the following sections.

CHAPTER 3: METHODOLOGY

3.0 Introduction

This section disucsses the research methodology employed to achieve the study objective established. It begins with the research design and sampling design used, moving on to the method of collecting data. The tools used for examining the data are going to be addressed.

3.1 Research Design

The design of the study aims to establish satisfactory and suitable structure for a research study (Sileyew, 2019). A quantitative approach is used to study the interrelations between AI usage and academic performance. It is an approach to testing objective concepts through studying the associations between variables (Creswell, 2017). It is an appropriate approach to be adopted for this study as the variables established can be measured in terms of measurement items, allowing the objective analysis of numerical information using statistical techniques. As a result, the connections between the independent variables (6 types of AI usages) as well as the dependent variable (academic performance) can be numerically measured.

Causal research is applied in this paper on the associations between AI usage and academic performance as it seeks to determine cause-and-effect relationships while delivering actual data on how different AI tool usage affects student academic outcomes. According to Decarlo (2018), causal research, or explanatory study seeks to determine the reason why certain phenomena behave in the manner they do. The objective of explanatory research is to analyse an instance or phenomenon to understand the relationship among constructs (Saunders et al., 2019). In this research, the causes include the six different uses of AI while the effect is the educational outcomes of pupils in HEIs.

3.2 Sampling Design

3.2.1 Target Population

A target population, the remaining portion of the overall population upon filtering, can be characterised as a collection of respondents who share particular characteristics (Creswell, 2017; Bartlett et al., 2001). It is far more precise than the overall population as it does not include characteristics that violate a study's assumption, setting, or objective (Asiamah et al., 2017). The target population for this research topic is students in higher education institutions. Quantitative research's target population is selected based on the individuals of the overall population who satisfy the eligibility criteria. As soon as a participant fulfils these requirements, he or she will be admitted. The capacity to respond holds minimal or no significance, therefore few criteria for selection can be applied (Asiamah et al., 2017). For this study, individuals are qualified to take part in the research if they are HEI students and are exposed to, or preferably, have been using AI.

3.2.2 Sampling Frame, Sampling Technique & Sample Size

A sampling frame is the collection of source materials from which the sample is drawn, aiming to serve as a method for selecting which individuals of the target population will be surveyed in the course of the research (Turner, 2003). Based on the International Association of Universities (IAU)'s World Higher Education Database (WHED) lists, there are currently approximately 21,000 approved or certified higher education institutions around the world

(International Association of Universities, 2024). Thus, the sample frame consists of students enrolled in all recognised higher education institutions.

A non-probability sampling technique, specifically a convenient sampling technique, is adopted in this study, whereby individuals of the population being studied are randomly selected for the research should they satisfy particular requirements, including geographical accessibility, availability at a specific time, ease of mobility, or desire to take part in the study (Farrokhi & Mahmoudi-Hamidabad, 2012).

The ten times rule suggests the minimum amount of samples should be 10 times the maximum number of arrowheads aiming at a latent variable in the PLS path model (Hair et al., 2022). Given that the number of arrowheads pointing at the dependent variable is 6 in this study, the minimum sample size will be 6 x 10 = 60. Furthermore, this research complied with Memon et al.'s (2020) guidelines on structural equation modelling (SEM), which demand a sample size of no less than 200 to produce accurate and valid results. The sample size calculations were complemented with the G*Power analysis tool. A minimum sample size of 146 was obtained using an effect size of 0.15, a 95% alpha value, and a probability of 0.80, in addition to six predictors.

3.3 Data Collection Methods

3.3.1 Primary Data

The techniques for gathering data are vital because the researcher's approach to analysis determine how the data acquired will be utilised and what interpretations it may deliver (Teherani et al., 2015; Wright et al., 2016). Surveys conducted through organised questionnaires are one of the essential data collection approaches given that they commonly involve collecting information on an extensive variety of variables from a broad and relevant group of participants (Hox & Boeije, 2005). Quantitative data can be obtained in a structured and systematic manner via a questionnaire, ensuring that the results are coherent and internally consistent for analysis (Roopa & Rani, 2012). Thus, to study the interrelations between various AI usages and academic performance, primary data will be collected through the use of an online survey. Through the distribution of the survey, data regarding the different uses of AI and the perceived academic performance of the respondents can be gathered structurally for further analysis.

3.3.2 Research Instrument

A questionnaire will be designed using Google Forms and distributed through social media platforms. The questionnaire consists of 4 sections. This study will follow ethical standards by obtaining full consent from all participants, ensuring that they understand the research's objective, procedures, potential risks, and benefits. Participants' personal information will also be protected. The respondents will be asked for their consent to participate voluntarily and have their data processed. Upon acknowledging the Personal Data Protection Notice, they will begin filling out the first section of the survey. The first part involves demographic questions including age, gender, race, current pursuing academic level, category of university, latest GPA, family income monthly range and location of residence. These demographic data could be beneficial during the analysis stage. The following sections consist of questions about the proposed independent and dependent variables. According to Joshi et al., (2015), the 7-point scale increases the range of options available, thereby enhancing the possibility of gaining more accurate data that better reflects reality (Joshi et al., 2015). Hence, the respondents will choose their answers that are presented in a Likert seven-point scale. Appendix A comprises the complete questionnaire.

3.3.3 Measurement of Scale

Measurement can be defined as the rule-driven allocation of numbers to items or occurrences. The fact that numbers are able to be allocated according to different principles results in various scales and measurements (Stevens, 1946).

3.3.3.1 Nominal Scale

The nominal scale offers the most liberal allocation of numbers (Stevens, 1946). The categories cannot be quantified or ranked in sequence (Marateb et al., 2014). The demographic questions regarding gender, race, category of university and location of residence are to be measured in the form of nominal data.

3.3.3.2 Ordinal Scale

The ordinal scale results from rank ordering (Stevens, 1946). An ordinal scale ranks individuals or objects based on the level to which they reflect an interest-related characteristic (Lawal & Lawal 2003). The demographic questions on age, current pursuing academic level, latest GPA and family monthly income range are to be measured in the form of ordinal data. Moreover, the remaining questions designed using the 7-point Likert scale are subject to be measured as ordinal data as well.

3.4 Proposed Data Analysis Tool

3.4.1 Partial Least Squares Structural Equation Modelling

The data collected in this study are to be run and analysed by the Partial Least Squares Structural Equation Modelling (PLS-SEM) using the Smart PLS software. SmartPLS is one of the statistical software used to analyse all the data collected (Wong, 2013). It enables the determination of statistical relationships between the independent variables and dependent variables. Excel will also be used for data checking, cleaning and coding. PLS-SEM analyses latent variables with composites (Cepeda-Carrion et al., 2019). It is a flexible approach to determining models of structural equations (Sarstedt et al., 2014). The analysis of PLS-SEM results takes place across two phases. Stage 1 explores the measurement models, with the evaluation differing based on whether or not the model incorporates reflective measurements, formative measures, or both of them (Hair et al., 2014). Upon successful analysis of the measurement model, the next phase (Stage 2) is to evaluate the structural model (Hair et al., 2014). The structural model is analysed through the evaluation of the model's explanatory and predictive capacity, as well as the relevance and significance of the path coefficients (Magno et al., 2022). It involves bootstrapping, a form of nonparametric analysis that looks into a parameter's variability by determining the dispersion of the estimates through resampling from the available sample information, rather than applying parametric assumptions for assessing the parameter's accuracy (Hair et al., 2019). In summary, Stage 1 investigates measurement principle, whereas Stage 2 emphasises structural analysis, which involves evaluating if structural connections have significance and value, as well as conducting hypothesis testing (Sarstedt et al., 2014).

3.5 Chapter Summary

Chapter 3 discussed the study and sampling design, data gathering approach and the data analysis technique adopted in this study. This study uses causal research to look into cause-and-effect connections between various AI tool usage and academic performance among students. A convenience sampling method is adopted to hand out the survey form, and the information gathered are to be analysed by using PLS-SEM software.

CHAPTER 4: DATA ANALYSIS

4.0 Introduction

This part reviews and assesses the outcomes that are necessary for the research questions and hypotheses presented. It starts with a descriptive analysis regarding the demographic information of the participants in terms of frequency and frequency percentage. Using Smart PLS software, an examination regarding the mean, median, standard deviation, kurtosis and skewness of the independent and dependent variables will be carried out. The reliability, validity, significance, variance inflation factor, r-square, hypothesis testing, and PLS predictions will be discussed.

4.1 Descriptive Analysis

This research successfully obtained 301 responses, exceeding the suggested sample size. As a result, the findings can be deemed as reliable and valid. The descriptive analysis presents the sample's demographic statistics and gives an outline of the variables in the paper. Frequency and percentage distributions display the demographic data, providing a comprehensive picture of the participants' information. Descriptive statistics, including standard deviations and means, were also used to summarise the central characteristics and variability of the key variables, establishing the basis to conduct subsequent inferential analyses.

4.1.1 The Demographic Information of Respondents

The demographic information of the participants is examined for better comprehension of the sample characteristics. Key demographic data including age, gender, academic background, and other relevant characteristics were analysed using frequency and percentage distributions.

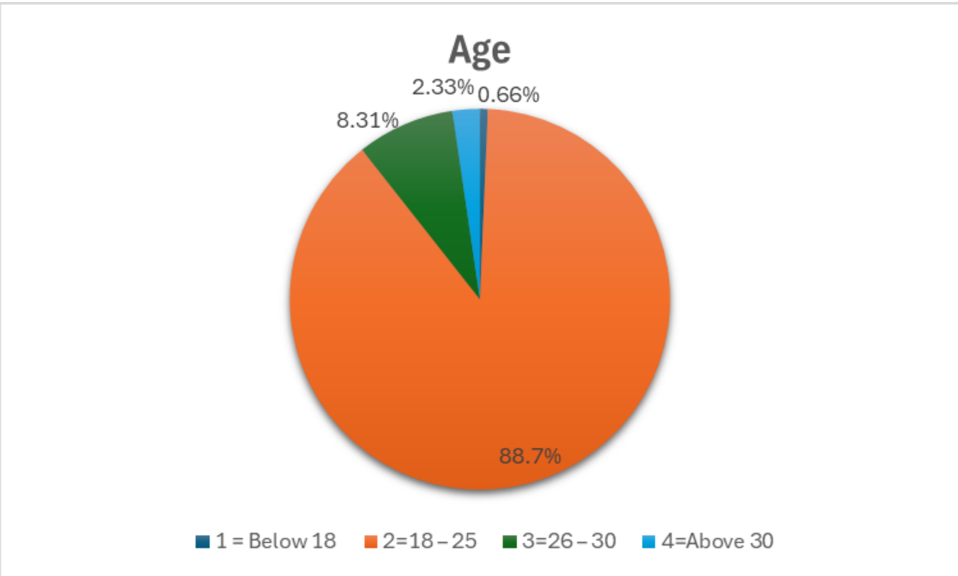
4.1.1.1 Age

Table 4.1 Age

Age	Frequency	Frequency Percentage %
Below 18	2	0.66
18 – 25	267	88.70
26 – 30	25	8.31
Above 30	7	2.32
Total	**301**	**100.00**

Source: Developed for the research.

Figure 4.1 Age



Source: Developed for the research.

Table 4.1 and Figure 4.1 demonstrate that the 18-25 age group comprises 88.7% of respondents, making it the largest cohort of the research survey. It is followed by 8.31% of the participants in the age group of 26-30, 2.33%

aged above 30 and a minority of 0.66% who were under 18.

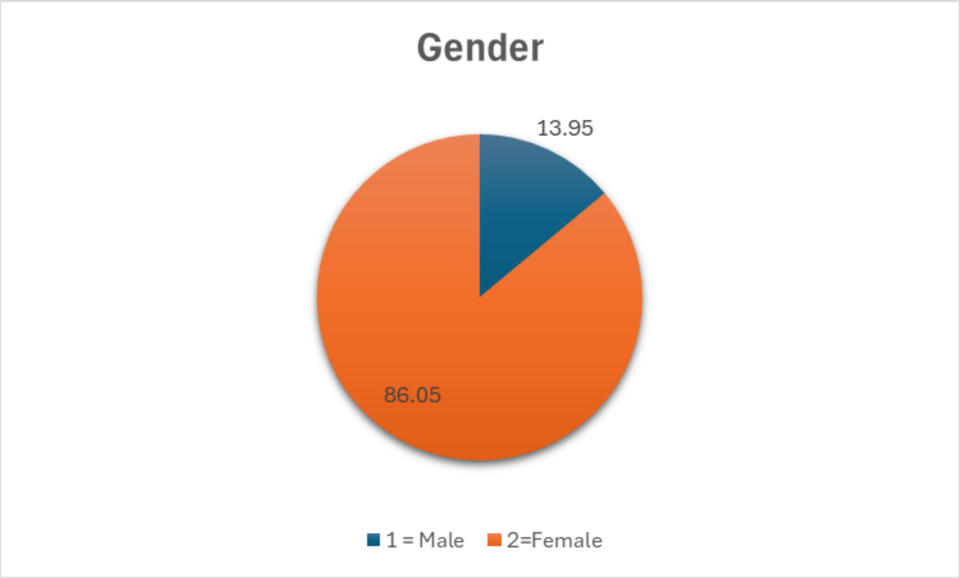
4.1.1.2 Gender

Table 4.2 Gender

Gender	Frequency	Frequency Percentage %
Male	42	13.95
Female	259	86.05
Total	**301**	**100.00**

Source: Developed for the research.

Figure 4.2 Gender



Source: Developed for the research.

According to Table 4.2 and Figure 4.2, females make up 86.05% of the survey respondents, while males represent a smaller portion at 13.95%.

4.1.1.3 Race

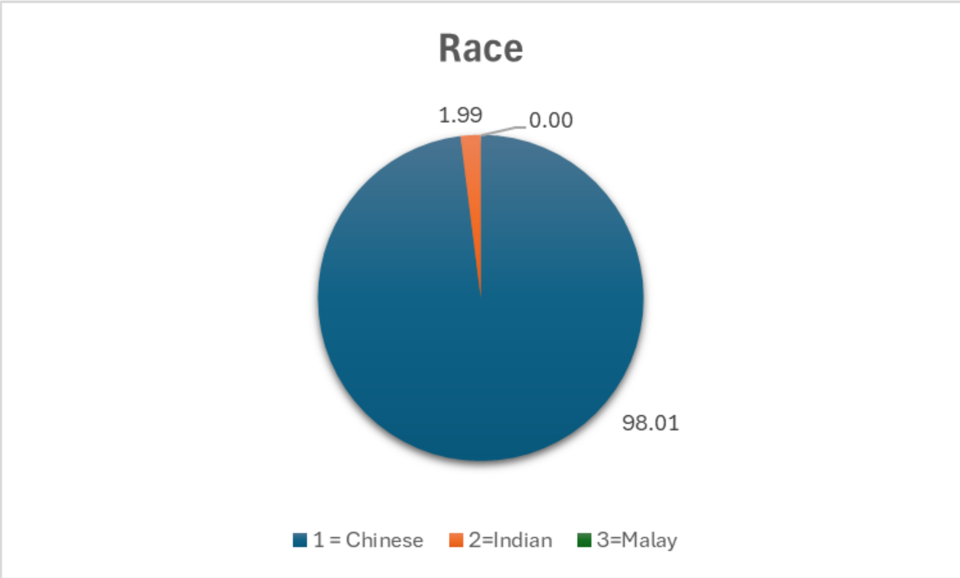
Table 4.3 Race

Race	Frequency	Frequency Percentage %
Chinese	295	98.01
Indian	6	1.99

Malay	0	0.00
Total	**301**	**100.00**

Source: Developed for the research.

Figure 4.3 Race



Source: Developed for the research.

Based on Table 4.3 and Figure 4.3, the majority of participants are Chinese, comprising 98.01% of the sample. This is followed by 1.99% Indian respondents, while no respondents were identified as Malay.

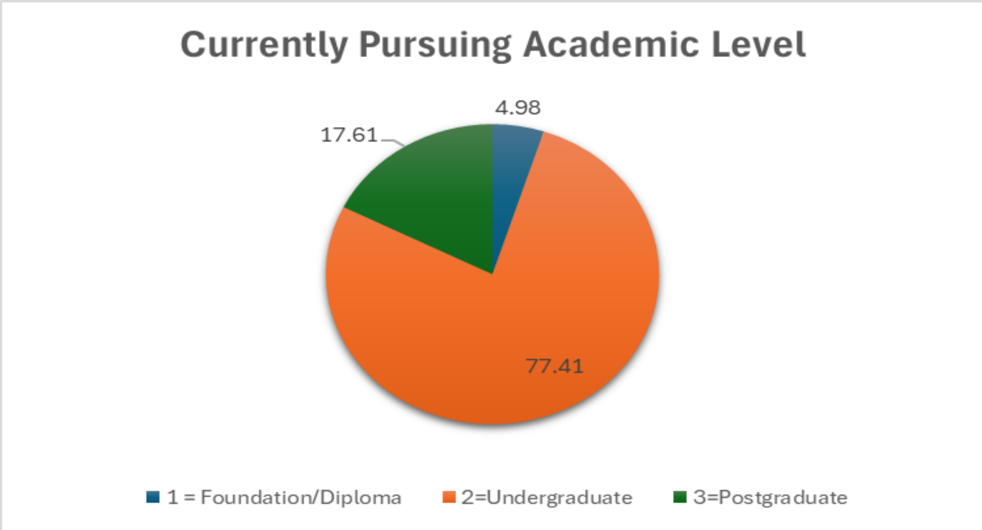
4.1.1.4 Currently Pursuing Academic Level

Table 4.4 Currently Pursuing Academic Level

Race	**Frequency**	**Frequency Percentage %**
Foundation/Diploma	15	4.98
Undergraduate	233	77.41
Postgraduate	53	17.61
Total	**301**	**100.00**

Source: Developed for the research.

Figure 4.4 Currently Pursuing Academic Level



Source: Developed for the research.

Table 4.4 and Figure 4.4 indicates that majority of the participants were undergraduates, making up 77.41% of the sample, with postgraduates at 17.61%, and those holding a foundation or diploma qualification at 4.98%.

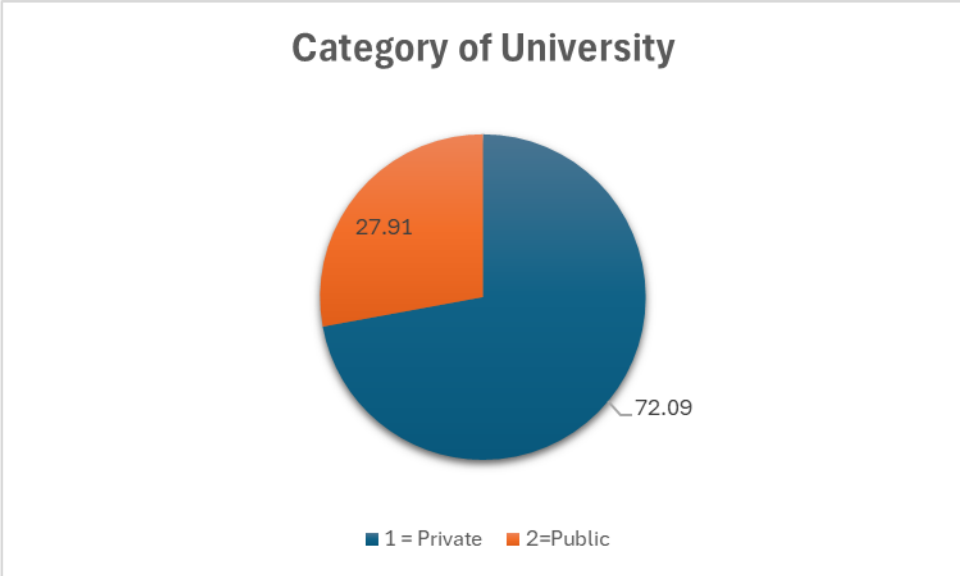
4.1.1.5 Categories of University

Table 4.5 Category of University

Category of University	**Frequency**	**Frequency Percentage %**
Private	217	72.09
Public	84	27.91
Total	**301**	**100.00**

Source: Developed for the research.

Figure 4.5 Category of University



Source: Developed for the research.

Table 4.5 and Figure 4.5 reveal that 72.09% of respondents are from private universities, representing the largest segment, while 27.91% are from public universities.

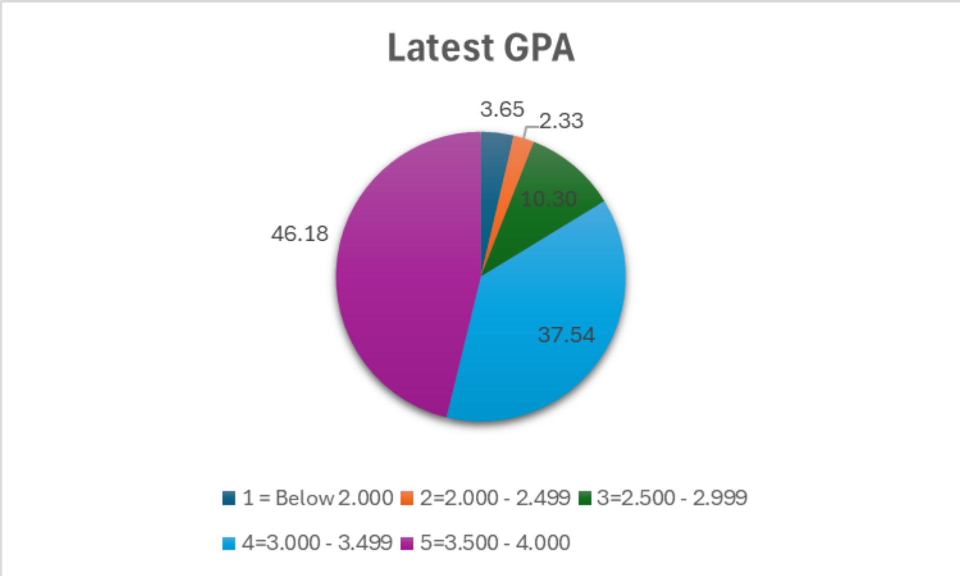
4.1.1.6 Latest GPA

Table 4.6 Latest GPA

Latest GPA	Frequency	Frequency Percentage %
1 = Below 2.000	11	3.65
2=2.000 - 2.499	7	2.33
3=2.500 - 2.999	31	10.30
4=3.000 - 3.499	113	37.54
5=3.500 - 4.000	139	46.18
Total	**301**	**53.82**

Source: Developed for the research.

Figure 4.6 Latest GPA



Source: Developed for the research.

As shown in Table 1 and Figure 1, 46.18% of respondents earned a GPA of 3.500 to 4.000, with 37.54% falling between 3.000 and 3.499. Respondents with GPAs between 2.500 and 2.999 constitute 10.30%, those with GPAs between 2.000 and 2.499 account for 2.33%, and 3.65% had GPAs less than 2.000.

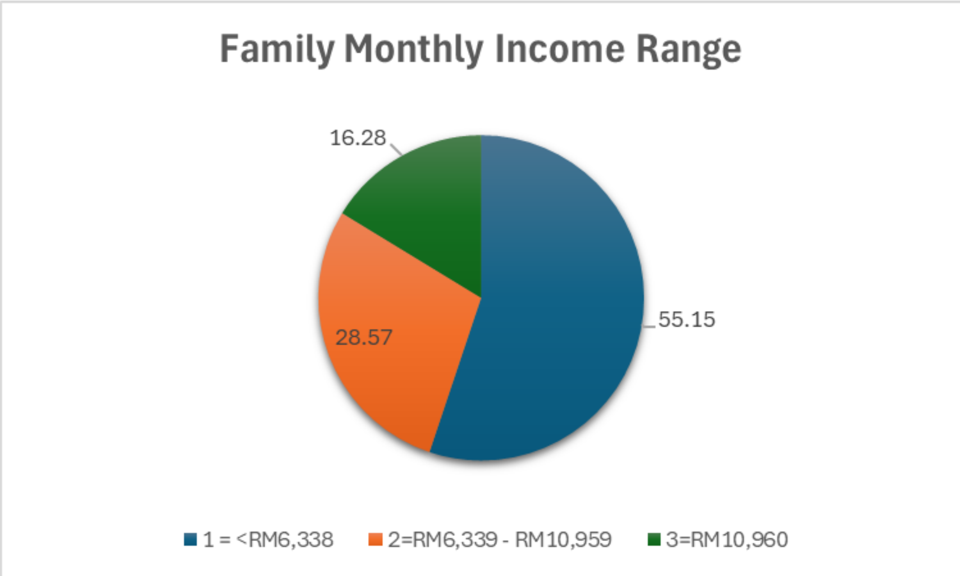
4.1.1.7 Family Monthly Income Range

Table 4.7 Family Monthly Income Range

Family Monthly Income Range	**Frequency**	**Frequency Percentage %**
<RM6,338	166	55.15
RM6,339 - RM10,959	86	28.57
RM10,960	49	16.28
Total	**301**	**100.00**

Source: Developed for the research.

Figure 4.7 Family Monthly Income Range



Source: Developed for the research.

According to Table 4.7 and Figure 4.7, 55.15% of participants with a monthly family income of below RM6,338; 28.57% earn between RM6,339 and RM10,959; and 16.28% earn over RM10,960.

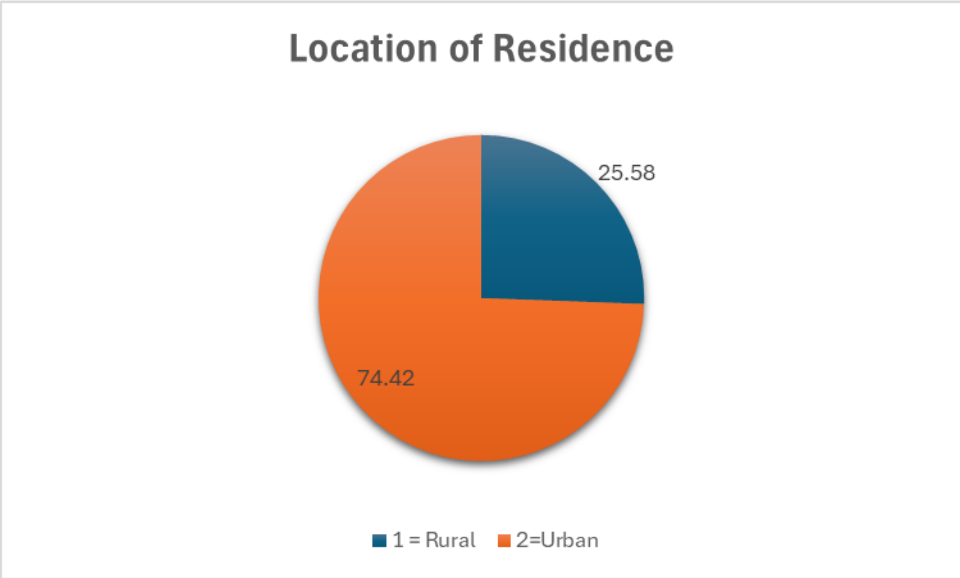
4.1.1.8 Location of Residence

Table 4.8 Location of Residence

Location of Residence	Frequency	Frequency Percentage %
Rural	77	25.58
Urban	224	74.42
Total	**301**	**100.00**

Source: Developed for the research.

Figure 4.8 Location of Residence



Source: Developed for the research.

As identified in Table 1 and Figure 1, 74.42% of respondents resided in urban areas, whereas 25.58% lived in rural areas.

4.1.2 Descriptive Statistics of Independent and Dependent Variables

Table 4.9 Descriptive Statistics of Independent and Dependent Variables

Name	Mean	Median	Standard deviation	Excess kurtosis	Skewness
RUE1	5.565	6	1.339	0.792	-1.027
RUE2	5.415	6	1.331	1.086	-1.151
RUE3	5.488	6	1.482	0.463	-0.983
RGR1	5.439	6	1.340	0.667	-0.947
RGR2	5.495	6	1.313	1.476	-1.130
EFT1	5.352	6	1.403	0.116	-0.768
EFT2	5.229	6	1.450	0.516	-0.970
EFT3	5.123	5	1.551	-0.085	-0.732
EFT4	5.150	6	1.558	0.024	-0.839
ETD1	5.355	6	1.411	0.569	-0.941
ETD2	4.983	5	1.598	-0.022	-0.836
ETD3	5.056	5	1.562	0.177	-0.862
INE1	5.449	6	1.436	0.480	-0.956
INE2	5.601	6	1.266	0.403	-0.916
INE3	5.073	5	1.600	-0.387	-0.663

INE4	5.445	6	1.367	0.534	-0.967
INE5	5.422	6	1.399	0.308	-0.913
INE6	5.645	6	1.285	1.521	-1.192
RID1	5.545	6	1.315	0.652	-0.965
RID2	5.648	6	1.207	1.825	-1.176
RID3	5.478	6	1.338	1.145	-1.107
AAC1	5.445	6	1.302	0.356	-0.787
AAC2	5.505	6	1.235	1.158	-1.011
AAC3	5.482	6	1.194	1.045	-0.927
AAC4	5.495	6	1.249	1.051	-0.982

Source: Developed for the research.

The descriptive statistics in Table 1 demonstrate that the mean values for every variable revolved around 5.5, with medians of 6, implying a slight left skew for the majority of variables. Skewness statistics reflect a moderate negative skew throughout the variables, especially for RID2 (-1.176) and INE6 (-1.192). Excess kurtosis values illustrate that, while most distributions are close to normal, some variables, such as RID2 (1.825), display occasional high values. Standard deviations range from 1.207 to 1.600, with INE3 having the highest standard deviation.

4.2 Inferential Analyses

The conceptual framework of this study was analysed in two phases using PLS-SEM. The measurement model was examined and then followed by the structural model in the subsequent stage.

4.2.1 Measurement Model Assessment

The initial phase of the analysis consisted of reviewing the measurement model to ensure the constructs' validity as well as reliability. Since the model's constructs were reflective, Cronbach's alpha and composite reliability were used to evaluate internal consistency. Convergent validity was determined using factor loadings and average variance extracted (AVE), and discriminant validity was shown using the HTMT ratio.

Table 4.10 Measurement Model

Construct	Item	Factor Loading	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Academic Performance	**AAC1**	0.885	0.883	0.888	0.919	0.74
	AAC2	0.860				
	AAC3	0.871				
	AAC4	0.824				
Efficient Use	**EFT1**	0.852	0.815	0.82	0.89	0.73
	EFT2	0.889				
	EFT4	0.820				
Extended Use	**ETD1**	0.893	0.885	0.885	0.929	0.812
	ETD2	0.904				
	ETD3	0.906				
Innovative Use	**INE1**	0.823	0.907	0.908	0.928	0.682
	INE2	0.813				
	INE3	0.831				
	INE4	0.842				
	INE5	0.834				
	INE6	0.810				
Regular Use	**RGR1**	0.924	0.825	0.825	0.919	0.851
	RGR2	0.921				
Reinformed Use	**RID1**	0.876	0.854	0.857	0.911	0.774
	RID2	0.883				
	RID3	0.880				
Routine Use	**RUE1**	0.901	0.876	0.878	0.924	0.801
	RUE2	0.910				
	RUE3	0.874				

Source: Developed for the research.

The results presented in Table 4.10 shows that all of the constructs' Cronbach's Alpha were higher than the recommended 0.7 threshold (Hair et al., 2017), indicating robust consistency reliability. The values range from 0.815 for Efficient Use to 0.907 for Innovative Use, indicating that each construct has high reliability. All constructs have composite reliability values (rho_a and rho_c) over the 0.7 threshold (Chin, 1998), reaffirming that that each construct is reliable. The CR values range from 0.82 for Efficient Use to 0.929 for Extended Use, indicating great internal consistency across constructs. Convergent validity was verified for all constructs, with each Average Variance Extracted (AVE) value exceeding the suggested 0.5 threshold (Fornell & Larcker, 1981). The AVE values vary from 0.682 for Innovative Use to 0.851 for Regular Use. The factor loadings for most of the item within the constructs met the accepted threshold of 0.7 for reliability of indicators (Hair et al., 2017). To exemplify, loadings of Regular Use and Routine Use show that their items have a strong link to their respective constructs, ensuring accurate measurement within the framework. The third item of Efficient Use (EFT3) did not meet the criteria and thus, were removed during the data cleaning process.

Table 4.11 Discriminant Validity: HTMT Matrix

Construct	1	2	3	4	5	6	7
Academic Performance							
Efficient Use	0.529						
Extended Use	0.432	0.831					
Innovative Use	0.607	0.665	0.622				
Regular Use	0.388	0.739	0.735	0.551			
Reinformed Use	0.603	0.58	0.609	0.784	0.588		
Routine Use	0.514	0.784	0.686	0.557	0.77	0.628	

Source: Developed for the research.

The outcomes displayed in Table 4.11 indicates that all variables in the study model fulfil the standards for discriminant validity of 0.80, showing that each construct is distinctive and sufficiently distinct from the others (Kline, 2023).

Table 4.12 Variance Inflation Factor

Constructs	VIF
Academic Performance	
Efficient Use	2.586
Extended Use	2.441
Innovative Use	2.248
Regular Use	2.118
Reinformed Use	2.168
Routine Use	2.322

Source: Developed for the research.

The results presented in Table 4.13 demonstrate that all VIF values were found to be less than 5, and no construct went above this threshold. This implies that multicollinearity is not a concern in this model as each construct serves independently to explaining the variance of the dependent variables.

4.2.2 Structural Model

In the subsequent phase, the structural model assessment is carried out to look into the hypothesised connections between constructs. It involved hypothesis testing to determine path significance, assessment of R^2 and adjusted R^2 values for explanatory power, and PLSpredict analysis to evaluate model predictive power.

Table 4.13 R-Square & R-Square Adjusted

	R-square	R-square adjusted
Academic Performance	0.377	0.365

Source: Developed for the research.

Table 4.14 depicts that the dependent variable, Academic Performance, had an R^2 value of 0.377, indicating that each of the independent variables in the model can explain 37.7% of the variance. This suggests an average degree of explanatory power, highlighting the relevance of the variables on educational performance. The R^2 adjusted result of 0.365 reflects the number of independent variables used in the analysis. This comparatively smaller value indicates the model's robustness and displays that, despite a considerable percentage of the variance is accounted for, there may be other variables that were not included in the model that could explain variations in academic performance.

Table 4.14 Structural Model

Hypothesis Testing	**Original sample (O)**	**Sample mean (M)**	**Standard deviation (STDEV)**	**T statistics (|O/STDEV|)**	**P values**	**5.00%**	**95.00%**	**Decision**
H1: Routine Use -> Academic Performance	0.182	0.181	0.080	2.276	0.011	0.057	0.322	Supported
H2: Regular Use -> Academic Performance	-0.092	-0.089	0.060	1.538	0.062	-0.189	0.003	Unsupported
H3: Efficient Use -> Academic Performance	0.149	0.152	0.083	1.784	0.037	0.003	0.279	Supported
H4: Extended Use -> Academic Performance	-0.056	-0.054	0.076	0.738	0.230	-0.179	0.070	Unsupported
H5: Innovative Use -> Academic Performance	0.280	0.279	0.077	3.636	0.000	0.151	0.403	Supported
H6: Reinformed Use -> Academic Performance	0.239	0.237	0.079	3.039	0.001	0.114	0.371	Supported

Source: Developed for the research.

In accordance with the outcomes generated from a bootstrapping procedure of 5000 samples, four hypotheses were supported, and two hypotheses were unsupported. H1, H3, H5, and H6 were supported, suggesting that Routine

Use, Efficient Use, Innovative Use, and Reinformed Use all have positive connections with Academic Performance. In contrast, neither Regular Use (H2) nor Extended Use (H4) exhibited positive associations with Academic Performance.

Table 4.15 PLSpredict Assessment

	Q^2predict	PLS-SEM_RMSE	PLS-SEM_MAE	LM_RMSE	LM_MAE	PLS-SEM_RMSE less LM_RMSE	PLS-SEM_MAE less LM_MAE
AAC1	0.277	1.113	0.890	1.166	0.922	-0.053	-0.032
AAC2	0.279	1.053	0.811	1.110	0.856	-0.057	-0.045
AAC3	0.262	1.030	0.817	1.070	0.844	-0.040	-0.027
AAC4	0.184	1.132	0.861	1.178	0.907	-0.046	-0.046

Source: Developed for the research.

PLSpredict was used to determine the predictability of the model. Table 4.16 shows that the PLS-SEM model consistently generated lower RMSE and MAE values across every indicator than the LM benchmark, exhibiting greater accuracy in prediction. In addition, all items had positive Q^2 Predict values ($Q^2 > 0$). Overall, the results suggest that the research model has strong predictive capacity to reflect reality and accurately predicting academic performance.

4.3 Chapter Summary

Chapter 4 presented the descriptive and inferential analyses of the study. Descriptive analysis involved frequency and percentage distributions for demographic information of the participants, as well as the variables' descriptive statistics. The inferential analysis examined the reliability and validity, examined the discriminant validity among constructs, measured multicollinearity using VIF, and presented R^2 and adjusted R^2 to show explanatory power of the model. Hypothesis testing further assessed the significance of proposed connections while PLSpredict determined the model's predictive power.

CHAPTER 5: DISCUSSION, CONCLUSION & IMPLICATIONS

5.0 Introduction

The segment outlines what was discovered in the earlier chapter's analysis. It will observe if there are advantageous associations in between the six independent variables and the dependent variable. The study's implications is to be explored as well. The final section will conclude by reviewing the paper's constriants along with suggestions for further studies.

5.1 Discussions of Major Findings

Table 5.1 Summary of the Results of Hypotheses Testing

Hypothesis Testing	Original sample (O)	T statistics (|O/STDEV|)	P values	Decision
H1: There is a positive association between the routine use of AI and the academic performance of higher education institution students.	0.182	2.276	0.011	Supported
H2: There is a positive association between the regular use of AI and the academic performance of higher education institution students.	-0.092	1.538	0.062	Unsupported
H3: There is a positive association between the efficient use of AI and the academic	0.149	1.784	0.037	Supported

performance of higher education institution students.				
H4: There is a positive association between the extended use of AI and the academic performance of higher education institution students.	-0.056	0.738	0.230	Unsupported
H5: There is a positive association between the innovative use of AI and the academic performance of higher education institution students.	0.280	3.636	0.000	Supported
H6: There is a positive association between the reinformed use of AI and the academic performance of higher education institution students.	0.239	3.039	0.001	Supported

Source: Developed for the research.

5.1.1 Routine Use of AI and Academic Performance

H1: There is a positive association between the routine use of AI and the academic performance of higher education institution students.

The results appear to validate this hypothesis ($\beta = 0.182$, t-value = 2.276, $p < 0.05$). The beta coefficient of 0.182 implies a favarouble association between routine usage of AI and academic performance, implying that using AI routinely enhances academic achievement. The p-value of 0.011 falls below the significance level, indicating statistical significance. The outcomes are in line with those of Singh et al. (2024), with AI usage considerably improving academic performance. Therefore, H1 is supported.

5.1.2 Regular Use of AI and Academic Performance

H2: There is a positive association between the regular use of AI and the academic performance of higher education institution students.

The results are in contradiction to this hypothesis ($\beta = -0.092$, t-value = 1.538, $p > 0.05$). The beta coefficient of -0.092 suggests a weak negative association, which indicates that regular usage of AI may not necessarily affect academic achievement and could possibly have a minor negative impact. The p-value of 0.062 surpasses the 0.05 threshold, suggesting that the association is not statistically significant. This could suggest that merely using AI on a regular basis, without any strategic plan or purpose, may not result in improvements in academic achievements. This is consistent with the findings of Fazil et al. (2024), which suggested that while there is a fundamental degree of faith in the favourable infleunce of AI tools on academic performance among pupils, the regularity of usage may not be an effective predictor. Hence, H2 is unsupported.

5.1.3 Efficient Use of AI and Academic Performance

H3: There is a positive association between the efficient use of AI and the academic performance of higher education institution students.

The results validate this hypothesis ($\beta = 0.149$, t-value = 1.784, $p < 0.05$). The beta coefficient of 0.149 reveals a postive connection, implying that students who use AI efficiently i.e. maximising its value in specific tasks, are prone to succeed academically. The p-value of 0.037 is less than 0.05, showing that the association is statistically significant. The results align with Ishaq's (2020) findings, which show that efficient use of ICT has a considerable and favourable effect on the academic outcomes of students. Thus, H3 is supported.

5.1.4 Extended Use of AI and Academic Performance

H4: There is a positive association between the extended use of AI and the academic performance of higher education institution students.

The findings are in disagreement with this hypothesis ($\beta = -0.056$, t-value = 0.738, $p > 0.05$). The beta coefficient of -0.056 demonstrates a weak negative association, and the p-value of 0.230 is more than the 0.05 significance level, implying a lack of meaningful relationship between extended usage of AI and academic performance. It implies using additional technological functions may not necessarily result in better educational outcomes. It might, however, reflect the concern of over relying on technology, which hinders students from developing essential cognitive skills crucial for academic success (Zhai et al., 2024). As a result, H4 is unsupported.

5.1.5 Innovative Use of AI and Academic Performance

H5: There is a positive association between the innovative use of AI and the academic performance of higher education institution students.

The findings substantially support this hypothesis ($\beta = 0.280$, t-value = 3.636, $p < 0.05$). The beta coefficient of 0.280 suggests a significant positive association, implying that students who use AI in novel ways i.e. finding inventive ways of using these technologies in their studies, see considerable benefits in their academic performance. The p-value of 0.000 falls far below the 0.05 significance level, implying that the association is statistically significant. This emphasises the necessity of adaptability and innovation in using AI tools for academic success. The outcomes confirm what has been discovered by Youssef et al. (2022), which suggested that the innovative and collaborative use of ICTs improved student academic performance. Hence, H5 is supported.

5.1.6 Reinformed Use of AI and Academic Performance

H6: There is a positive association between the reinformed use of AI and the academic performance of higher education institution students.

The results clearly validate this hypothesis ($\beta = 0.239$, t-value = 3.039, $p < 0.05$). The beta coefficient of 0.239 suggests a positive relationship, illustrating that students who are involved in reinformed usage of AI i.e. continually researching technology for future uses, perform better academically. The p-value of 0.001 is less than 0.05, demonstrating the statistical significance of such association. The results confirm Park and Weng's (2020) findings that students with greater autonomy and interest in exploring technology are more likely to obtain control of their process of learning with technology, resulting in a significant beneficial impact on their academic performance. Thus, H6 is supported.

5.2 Implications of the Study

The discoveries of this paper carry important managerial and academic implications for policymakers and educators. First, the favourable association between routine AI use and academic performance suggests that educational institutions should incorporate AI technologies into their educational programmes. AI-powered learning can help educators improve the performance of students (Ellikkal & Rajamohan, 2024). Furthermore, the efficient, innovative and reinformed use of AI boosts learning outcomes, emphasising the vitality of AI tools that are practical, inventive, and enable students to explore further. Educators should prioritise promoting the adoption of AI that enhance student performance and facilitate students' academic processes.

Nevertheless, the absence of significance in the regular and extended use of AI implies that merely increasing AI usage without specific educational objectives or approaches might not yield positive outcomes. Educational institutions should therefore prioritise practical usage over regular adoption of AI. Moreover, overreliance on extended features of AI without any particular goal may not improve student performance. Zhai et al. (2024) discovered that extensive reliance on AI has an impact on cognitive abilities, as individuals prefer quick and appropriate answers over slow ones that are restricted by individuals' capability. Policymakers and educators should thus advise students in using AI technologies to complement conventional approaches to learning while fostering problem-solving and critical thinking skills.

5.3 Limitations of the Study

Although this paper offers meaningful perspectives, it is vital to recognise its constraints. The first limitation is the limited number of variables examined with regard to academic performance and usage of AI. While this study focused on multiple usage of AI, other relevant elements such as students' digital competency, AI tool accessibility, and psychological variables such as interest and motivation were not covered. Other types of AI usages such as personalised use, collaborative use, assessment use and many more remained unexplored. Furthermore, this paper employed a cross-sectional approach, with data obtained only at a particular moment. Nevertheless, AI technologies and their incorporation into education are constantly developing, and students' use behaviours could change over time. Ultimately, the sample for this study is primarily composed of pupils from HEIs, which limits the generalisation of the findings to other demographics such as high school pupils or individuals who participate in programmes for professional development. These limitations are highlighted; nonetheless, they are not reducing the significance of the discoveries, but rather establish essential foundations for subsequent research.

5.4 Recommendations for Future Research

Future studies could expand the scope by investigating other additional factors to present a more comprehensive picture of how AI impacts student achievement. Longitudinal research is recommended to provide greater detail regarding AI's long-term impact on academic performance. In addition, expanding the demographic groups such as high-school students could provide further insight regarding how the different usage of AI impacts academic performance. Such attempts would make a crucial contribution to both educational research and practical development of technology in education.

5.5 Chapter Summary

The final section has discussed the major findings from the paper, validating the associations between AI usage and achievement in education. While accepting its limitations, the study facilitates the value of ongoing study to obtain a more thorough comprehension of the possibilities of AI technologies in improving and changing the future trend of academic performance.

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APPENDIX A

Questionnaire

Demographic Questions	Options
Age	Below 18
	18 – 25
	26 – 30
	Above 30
Gender	Male
	Female
Race	Malay
	Chinese
	Indian
	Others, please state
Academic Level	Foundation/Diploma
	Undergraduate
	Postgraduate
Category of University	Public
	Private
Latest GPA	Below 2.000
	2.000 - 2.499
	2.500 - 2.999
	3.000 - 3.499
	3.500 - 4.000
Family Monthly Income Range	<RM6,338
	RM6,339 - RM10,959
	>RM10,960
Location of Residence	Rural
	Urban

Construct	Item	Original Items	Source	Modified Items
Routine Use (RUE)	RUE1	My use of [technology] has been incorporated into my regular work schedule.	Saga & Zmud (1994) as cited in Sundaram et al. (2009)	My use of AI has been incorporated into my regular academic schedule.
	RUE2	My use of [technology] is pretty much integrated as part of my normal work routine.		My use of AI is pretty much integrated as part of my normal academic routine.
	RUE3	My use of [technology] is a normal part of my work.		My use of AI is a normal part of academic work.
Regular Use (RGR)	RGR1	On average, how frequently have you been using [technology] for your work?	Taylor & Todd (1995) as cited in Sundaram et al. (2009)	On average, how frequently have you been using AI for your academic work?
	RGR2	Since it became available, how frequently have you been using [technology] for your job?		Since AI became available, how frequently have you been using it for your academic work?
Efficient Use (EFT)	EFT1	I am using [technology] to its fullest potential for supporting my	Jones et al. (2002) as cited in Sundaram et al. (2009)	I am using AI to its fullest potential to support my own academic work.

		own work.		
	EFT2	I am using all capabilities of [technology] in the best fashion to help me on the job.		I am using all the capabilities of AI in the best fashion to help me in my academic work.
	EFT3	I doubt that there are any better ways for me to use [technology] to support my work.		I doubt that there are any better ways for me to use AI to support my academic work.
	EFT4	My use of [technology] on the job has been integrated and incorporated at the highest level.		My use of AI in academic work has been integrated and incorporated at the highest level.
Extended Use (ETD)	ETD1	In a typical one-month period, I often use most of the features of the ERP system installed in my organisation to support my work.	Schwarz (2003) as cited in Po-An Hsieh and Wang (2007)	In a typical one-month period, I often use most of the features of AI available to support my academic work.
	ETD2	In a typical one-month period, I often use more features than the average user of the ERP system		In a typical one-month period, I often use more features than the average user of AI available to

		installed in my organisation to support my work.		support my academic work.
	ETD3	In a typical one-month period, I often use more obscure aspects of the ERP system installed in my organisation to support my work.		In a typical one-month period, I often use more obscure aspects of AI available to support my academic work.
Innovative Use (INE)	INE1	I intend to explore new IT for potential application in my work context.	Nambisan et al. (1999)	I intend to explore new AI for potential applications in my academic work context.
	INE2	I intend to explore new IT for enhancing the effectiveness of my work.		I intend to explore new AI to enhance the effectiveness of my academic work.
	INE3	I intend to spend considerable time and effort this year in exploring new IT for potential applications.		I intend to spend considerable time and effort this year in exploring new AI for potential applications.
	INE4	I explore how I	Saeed et al.	I explore how I

		can use SIS to manage my academic tasks	(2008)	can use AI to manage my academic tasks.
	INE5	I explore new uses of SIS to manage my academic tasks		I explore new uses of AI to manage my academic tasks.
	INE6	I explore how SIS can better support my academic needs		I explore how AI can better support my academic needs.
Reinformed Use	RID1	I intend to continue exploring how [system name] can be used in my work tasks.	Maruping and Magni (2015)	I intend to continue exploring how AI can be used in my academic tasks.
	RID2	I intend to continue exploring other ways that [system name] may enhance my work effectiveness.		I intend to continue exploring other ways that AI may enhance my academic work effectiveness.
	RID3	I intend to continue spending time and effort in exploring [system name] for potential applications to		I intend to continue spending time and effort in exploring AI for potential applications to my academic

		my work.		studies.
Academic Performance	AAC1	I feel confident in my ability to learn this material.	Williams & Deci (1996) as cited in Self-Determination Theory (2024)	I feel confident in my ability in academic learning.
	AAC2	I am capable of learning the material in this course.		I am capable of learning in an academic setting.
	AAC3	I am able to achieve my goals in this course.		I am able to achieve my academic goals.
	AAC4	I feel able to meet the challenge of performing well in this course		I feel able to meet the academic challenge of performing well.

APPENDIX B

Questionnaire Cover Page

The Interrelations between Artificial Intelligence (AI) Usage and Academic Performance

Dear esteemed respondents

This is Chin Wie Jane (Student ID: 2105802), an undergraduate student of the Bachelor of International Business (Hons) from Universiti Tunku Abdul Rahman (UTAR). I am conducting this survey as part of my research project, which aims to examine the interrelations between Artificial Intelligence usage and academic performance of higher education institution students.

The survey will take around 3 - 5 minutes to complete. Rest assured that all information provided will be treated with the utmost confidentiality. Your responses will only be used for the purpose of this research project and will not be shared with any third parties.

Thank you for considering taking part in this survey. Your participation is greatly appreciated.

Should you have any enquiries, please do not hesitate to contact me.

Yours faithfully
wiejane1024@1utar.my

APPENDIX C

Ethical Clearance Approval Official Letter

UNIVERSITI TUNKU ABDUL RAHMAN DU012(A)
Wholly owned by UTAR Education Foundation Co. No. 578227-M

Re: U/SERC/78-352/2024

9 September 2024

Dr Fitriya Binti Abdul Rahim
Head, Department of International Business
Faculty of Accountancy and Management
Universiti Tunku Abdul Rahman
Jalan Sungai Long
Bandar Sungai Long
43000 Kajang, Selangor

Dear Dr Fitriya,

Ethical Approval For Research Project/Protocol

We refer to your application for ethical approval for your students' research project from Bachelor of International Business (Honours) programme enrolled in course UKMZ3016. We are pleased to inform you that the application has been approved under Expedited Review.

The details of the research projects are as follows:

No.	Research Title	Student's Name	Supervisor's Name	Approval Validity
1.	Strategic Approaches to Enhance Consumer Engagement and Traction Through Livestreaming Content: A Comparative Analysis of Effective Tactics and Best Practices	Adeline Kong Qing Qing	Pn Ezatul Emilia Binti Muhammad Arif	9 September 2024 – 8 September 2025
2.	Factors Influencing Customers Acceptance of Malaysian Traditional Bank's Digital Channels	Chan Huey Teng	Dr Tee Peck Ling	
3.	Relationship Marketing Affecting the Customer Experience in Using AI-Chatbot	Chan Pei Yee	Dr Yeong Wai Mun	
4.	Factors that Influence Employee Performance in the Workplace	Chen Kar Him	Dr Komathi a/p Munusamy	
5.	Social Media Advertising Format that Affect Consumer Behaviour in Malaysia	Cheong Yi Qian	Dr Fok Kuk Fai	
6.	Consumer Intentions to Switch Accommodations from Traditional Hotels to Airbnb	Chia Rong Wei	Dr Law Kian Aun	
7.	Engulfed by Recommendation Systems: Walking Away Empty-handed Becomes a Challenge	Chin Kai Ning	Pn Ezatul Emilia Binti Muhammad Arif	
8.	The Interrelations Between Artificial Intelligence (AI) Usage and Academic Performance	Chin Wie Jane	Dr Low Mei Peng	
9.	Factor Affecting University Students' Behavioural Intention to Use ChatGPT for Academic Purpose	Chock Yee Fai	Pn Farida Bhanu Binti Mohamed Yousoof	
10.	The Impact of ESG Initiatives on Green Product and Consumer Purchase Intentions	Choi Yoon Qi	Dr Foo Meow Yee	
11.	Factors Influencing Gender Entrepreneurial Intention Among Malaysian Undergraduate Students	Chong Chean You	Dr Kalaivani a/p Jayaraman	
12.	The Influence of Technological Infrastructure on the Success of Digital Reading Platforms Globally Among Students	Chong Li Xian	Dr Komathi a/p Munusamy	

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The conduct of this research is subject to the following:

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

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

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

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

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

Thank you.

Yours sincerely,

Professor Ts Dr Faidz bin Abd Rahman
Chairman
UTAR Scientific and Ethical Review Committee

c.c Dean, Faculty of Accountancy and Management
Director, Institute of Postgraduate Studies and Research

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