

THE IMPACT OF AI SUCH AS CHATGPT ON
STUDENTS' LEARNING AND DAILY LIFE: A
STUDY BASED ON UNIVERSITY STUDENTS

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BY

CHIN YIN TONG

A final year project submitted in partial
fulfilment of the requirement for the
degree of

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

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LIST OF ABBREVIATION

AI	Artificial Intelligence
AIED	Artificial Intelligence in Education
AVE	Average Variance Extracted
CAGR	Compound Annual Growth Rate
CAI	Computer-Assisted Instruction
CASI	Convenience and Social Influence
CB-SEM	Covariance Based Structural Equation Model
DL	Deep Learning
DL	Digital Literacy
GPT	Generative Pre-trained Transformer
HTMT	Heterotrsit-Monotrait
ITS	Intelligent Tutoring Systems
ITUA	Intention to Use AI
LLMs	Large Language Models
NLP	Natural Language Processing
PLS-SEM	Partial Least Squares Structural Equation Modeling
PU	Perceived Usefulness
SEM	Structural Equation Modeling
SLE	Students' Learning Efficiency

TA	Technology Acceptance
TAM	Technology Acceptance Model
TPB	Theory of Planned Behaviour
TSE	Technological Self-Efficacy
UTAUT	Unified Theory of Acceptance and Use of Technology
VIF	Variance Inflated Factors

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PREFACE

Being a student in the higher education system, which is undergoing rapid changes, the rise of the powerful AI tool like ChatGPT has been both a remarkable and scare event at the same time. There is no denying that these tools have become a part and parcel of both our academic and non-academic lives and are providing us with the benefits of being more efficient, productive, and having instant information as well as the support of learning and being innovative. The present report is the result of the ongoing need to comprehend and to keep track of these radical changes in learning and student life in general.

This is a step that aims at going further than mere stories about the phenomena and the hype created by the media to conduct an empirical investigation into the application of conversational AI tools by students and the real impact on my fellow students and me. I would like to see the report not only meet the requirements of the academic world but also give precious knowledge to students, educators, institutions, and decision-makers, as we all together learn to share the space with this powerful new technology.

ABSTRACT

AI tools are a major factor in the transformation of learning into a more efficient and accessible process, at the same time, students are benefiting from AI as they can report that their productivity has increased. When students perceive AI applications as important and usefulness in enhancing their learning efficiency and academic performance, they will be more persuaded to adopt such technologies. With the aid of the digital literacy of students, their confidence and skills to handle AI-based learning tools are reinforced. Positive perceptions of students are connected with positive attitudes, which are functional for affecting their willingness to adopt AI-driven learning tools. Using digital learning tools conveniently is a motivational factor for students to embrace ChatGPT in their learning processes to revamp academic outcomes. By dint of social influence through positive social norms and advocacy of peers, students' intention to adopt ChatGPT is affected.

Keywords: Artificial Intelligence, ChatGPT, Perceived Usefulness, Digital Literacy, Convenience, Social Influence

CHAPTER 1: RESEARCH OVERVIEW

1.0 Introduction

This chapter introduces Artificial Intelligence (AI) technologies, particularly large language models (LLMs) like ChatGPT have become widely accessible and increasingly adopted by students for tasks ranging from drafting essays to problem solving. This study explores how such tools influence the learning efficiency and daily lives of students.

1.1 Research Background

1.1.1 Introduction of Artificial Intelligence

Artificial Intelligence (AI) is a technology that makes computers and machines mimic human learning, perception, decision making, problem solving, and autonomy (Stryker & Kavlakoglu, 2024). In education, AI (often referred to as AIED) is a subfield of educational technology that leverages techniques such as generative AI chatbots like ChatGPT to develop adaptive learning environments, individualize teaching and aid the performance of functions such as tutoring, grading and feedback (University of San Diego, 2025). Applications, devices using AI can see object and identify it. They are able to comprehend and reply to humans. They are capable of learning from the new and from experience. They can provide specific recommendations to users and

professionals. They are intelligent and should function autonomously without the presence of a human (Stryker & Kavlakoglu, 2024).

The 21st century has been a stage to a technological revolution never seen before and among other things, AI (artificial intelligence) has been the strongest power in changing industries, economic, social, and ethical aspects (Brandao and Wang, 2025, 2024). AI has shown its power by being a great helper to the people, allowing them to perform a variety of tasks in a faster and more efficient manner. In the medical field, AI plays an important role in human drug research, medical imaging, medical services innovation, and patient health management. In the educational sector, the use of AI can support students in various ways such as intelligent process support, teaching assistant intellectual support, education and management, and building a smart environment. Moreover, the application of AI in the finance sector is very beneficial for banking, insurance, capital markets, business, and financial support for the industry. On top of that, its implementation in the computer industry aids human beings in maintaining network security, conducting systematic reviews, and performing data analysis.

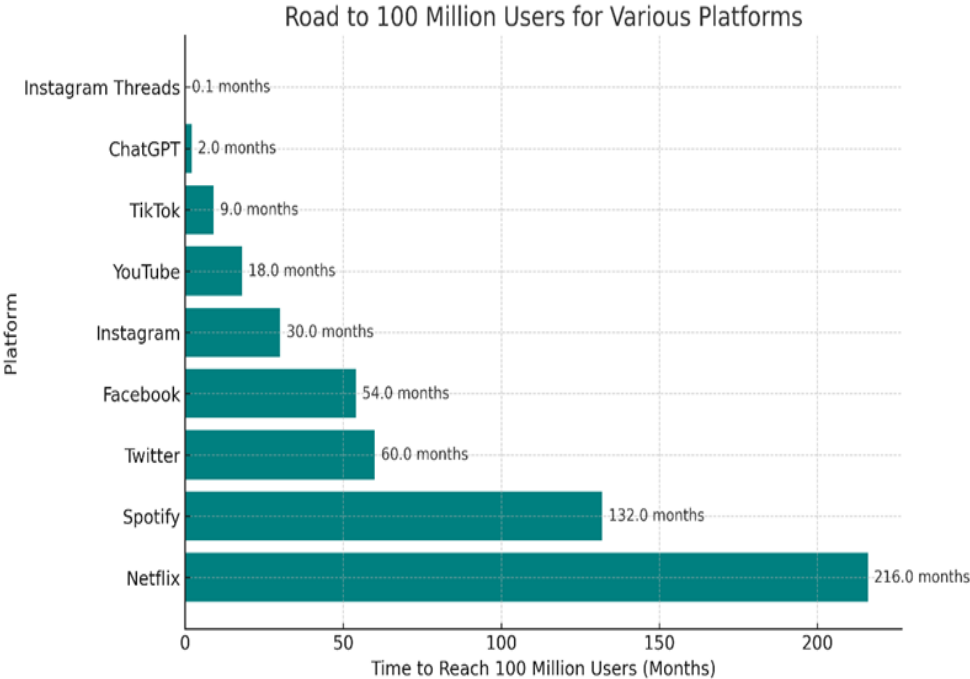
AI's involvement in education can be traced back to when mainframe computers first began to aid in computer-assisted instruction in the 1960s, and continued until 2005 when Intelligent Tutoring Systems began providing individualized feedback (Guo et al., 2021). In the 2010s, the widespread growth of big data and deep learning supported the emergence of modern-day edtech tools, including adaptive platforms and chatbots. The adoption of generative AI tools (e.g., ChatGPT) for tutoring and content creation provided further impetus for these types of developments. ChatGPT, a sophisticated language model by OpenAI that was launched in November 2022 and is based on the Generative Pre-trained Transformer (GPT) technology, still marks a turning point in this progress and at the same time has caused a huge transformation in the traditional learning paradigm with its swift adoption by students within months of its launch (Kamalov et al., 2023). It operates through their top-tier large language

models (LLMs) of the GPT-3.5 and GPT-4 families, and leverages recent accomplishments in deep learning (DL), in combination with state-of-the-art natural language processing (NLP) methods, such as the self-attention mechanism and the use of transformers (Kalyan, 2023). Consequently, machine learning and data analytics are the building blocks of contemporary AI that are reshaping education by evaluating students' performance so as to create personalized content, foresee difficulties, and increase participation (Ma'amor et al., 2024). Digital Learning Institute (2024) states that this platform is now accessible to everyone; one can simply put in their prompts and instantly receive answers derived from their questions. A few words are all you need to get answers and citations in seconds; they will be generated on your screen for you to view, and if necessary, you can delve further.

At the same time, as a result of the COVID-19 pandemic that affected almost all of the world, much of society's daily activities were interrupted. To curb the virus's spread, they stopped social events and travel. The pandemic messed up regular in-person classes, and schools shut down for a bit (Toro et al., 2021). The pandemic hastened the digitalization of education as online learning and dependence on digital resources became a normal way of life, which established the fertile ground and favorable environment towards the integration of advanced AI tools (Pantelimon et al., 2021). Its capability of producing text that sounds like a human, responding to complicated questions, and aiding in a great number of tasks has caused its fast and widespread adoption ranging from various fields, with education being the one sector mostly affected (Ortiz, 2022). The students, mainly those who are in the above-mentioned technological wave, have been using AI tools for research, writing, coding, and learning purposes. These technologies have not only altered the manner in which students acquire and comprehend information but also have had a profound impact on the whole learning process, research, and academic cooperation in terms of their nature.

It is clear that Hu (2023) pointed out that the launch of extremely advanced AI technologies, particularly such as the conversational AI systems like ChatGPT which gained 100 million users in only two months, is a clear evidence of a strong influence of AI on the higher education sector and its adoption which is steadily increasing. By the end of October 2025, ChatGPT was already among the top Generative AI chatbot companies, taking over a stunning 81.39% of the market (Singh, 2025). This giant presence makes it clear that it is also the leading player in the AI search market where its share is also impressive at 81.13%. The rapid growth in popularity of these tools demonstrates that, indeed, people want tools that are easy to use and can help them make decisions and be more productive.

Figure 1.1
Time To Reach 100 Million Users for Various Platforms

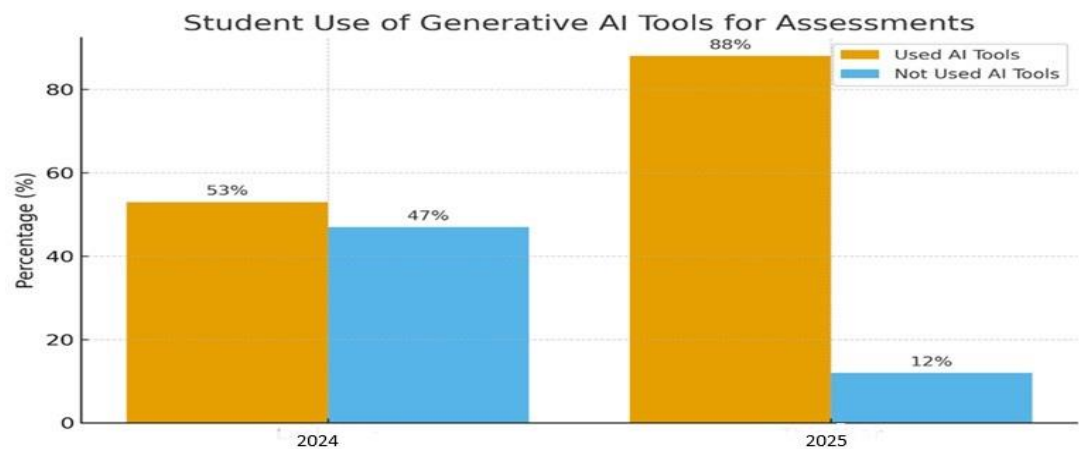


Note. This figure shows the time taken for different platforms to attain the milestone of 1 million users. Adapted from Singh ,2025, Latest ChatGPT Users Stats 2025 (Growth & Usage Report).\

Recent stats show a huge 88% of students have used AI tools like ChatGPT for schoolwork. Among the diverse uses, the generative AI is mainly to clarify the concepts, concisely narrate the articles and recommend research topics. The share of students who did not engage generative AI for their evaluations in these terms has decreased from 47% in the previous year to a mere 12% this year. (Student Generative AI Survey 2025 - HEPI, 2025). According to the studies, students can engage with AI tutors, writing assistants, assignment partners and textbook inquiries (Baidoo-Anu D et al., 2023; Bhandari et al., 2023; Rane et al., 2023). This is not a technological improvement, but a shift in the relationship between the learners and the acquisition of knowledge.

Figure 1.2

Student Use of Generative AI Tools for Assessments



Note. This figure illustrates an unprecedented rise in the usage of generative AI tools among undergraduate students from the rates recorded in 2024 compared to 2025. Data from Student Generative AI Survey 2025 - HEPI, 2025.

Basically, AI's use in education has been a game-changer. It is changed how we teach and learn, from making learning fit each person to automating tasks. AI is not meant to replace teachers or old-school ways but to help out. Teachers can use AI to track student development while they use it to improve their teaching methods through their own required interventions. The AI system delivers essential student performance feedback which helps teachers create efficient teaching methods. The educational system already shows how AI creates personalized learning experiences and offers better resource access and improved operational performance.

1.1.2 Current Impact of Artificial Intelligence in Education

The application of artificial intelligence is significantly changing the educational sector, bringing along a new era of innovation and transformation through the provision of tools that adapt to the individual needs of learners, reduce the workload of the administration, and offer data analytics as one of the main ways of getting the insights (Clugston, 2024). The impact of AI has been felt through both general and higher education, where it has affected students' academic progress in a dual manner of offering opportunities and posing challenges (Vieriu & Petrea, 2025). AI is applying its magic in the transformation of the teaching-learning process by both the personalization of learning experience and the introduction of intelligent tutoring systems (Wang et al., 2024). Besides the vast advantages, there still remain ethical issues, data privacy worries, and the challenge of equitable access which are, nevertheless, considered as downsides of AI (Willie, 2024).

AI has been a valuable partner in various aspects of student life, offering on their journey from learning through research and writing to problem-solving and language acquisition. Personalized tutoring, instant feedback, and adaptive learning are the main consequences of AI that in turn lead to greater student

engagement and learning (Vieriu and Petrea, 2025). According to Kurt. (2021), artificial intelligence via adaptive learning technologies can evaluate the strengths and weaknesses, the learning pace and preferences of a student. This information can feed AI that will suggest personalized lesson plans and resources besides the one that the student is following by the teacher so that the student gets instruction tailored to his/her learning style. With this, the student can move at his or her pace which helps understanding and retention of the material. For instance, one of the major areas that AI has been used in writing instruction is evaluation where students get real-time feedback, and the feedback will help students continuously refine their work (Ruwe & Mayweg-Paus, 2023). AI technologies, like Automated Writing Evaluation systems, act as facilitators of self-directed learning via quick and efficient feedback thus providing merits in off-line learning situations (Youn et al., 2025). Active engagement in self-directed learning with such tools as ChatGPT makes the students more motivated and is the reason for a better understanding of the academic material (Giray et al.,2025; Guan et al., 2020; Kamalov et al., 2023).

Many students find writing research papers a very demanding undertaking, especially with organizing their ideas, locating appropriate references, and following the academic styles (Li et al., 2024). It is a major undertaking for the students of the English language and non-English language, especially those enrolled in a graduate program or final-year undergraduate studies. The challenge in writing research papers has led to the proposal of artificial intelligence (AI) as a solution to the problem in the language teaching context that has been growingly integrated over the past few years. AI-powered writing tools like Grammarly provide immediate feedback on spelling, punctuation, and grammar and thereby work with students in expressing their ideas more clearly (Gerlich, 2025). Further, the AI-driven tool can be of great help to students in locating pertinent literature rapidly and accurately, whereas the citation management software like EndNote can ease the reference handling task (Orhan Sungur & Ozkan Seyhan, 2014). It reduces the time and effort required for the

research process as it helps in quicker and better synthesizing of information, supporting literature review, and generating hypothesis, as well as in the writing process and acquisition of language through grammar correction, style enhancement, and structure guidance. The AI tools are said to be a boon for the English learners in terms of personalization and accessibility, which is consistent with the principles of Universal Design for Learning (UDL).

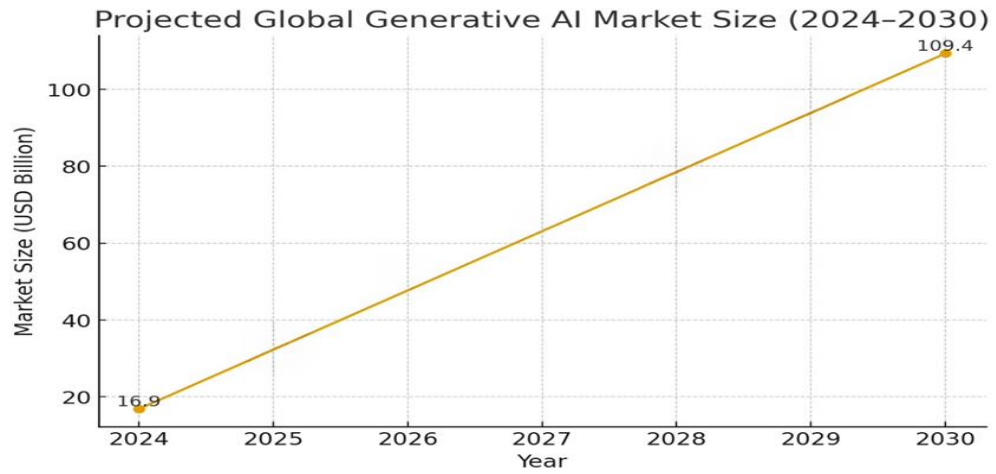
1.1.3 Trends of Artificial Intelligence in Education

The field of education is undergoing transformation driven by AI with several noticeable trends emerging. This shift is due, to the Generative AI revolutionizing the development of classroom materials providing tools that enhance both teaching and learning processes (Creely & Blannin ,2024). This cutting-edge technology utilizes machine learning algorithms to generate creative content, including text and images by using extensive datasets and particular prompts (Bartlett et al., 2025). The rapid increase in AI usage is clearly evident in education and even, at the secondary level as an increasing number of students report utilizing these tools for various academic tasks (Black & Tomlinson, 2025). Learners gain from tailored material that adjusts according to their advancement promoting both engagement and understanding. This improvement, in results can be linked to the varied methods students use to interact with content; although some thrive using conventional study techniques others benefit more from video or audio resources (Kanchon et al., 2024). The deployment of high-quality study materials enabled by generative AI technologies is expected to greatly influence the evolution of education (Pang & Wei, 2025). These technologies enable students to focus on their points while also helping to overcome their weaknesses. Moreover generative AI tools frequently connect with progress-monitoring applications offering a complete summary of personal accomplishments and performance thus enabling improved tracking of progress (Serhii Uspenskyi, 2025).

AI has been integrated into settings for many years subtly driving learning management platforms like Google Classroom, Canvas and Turnitin (Abrams, 2025). Global market reports in Artificial Intelligence 2030 indicate that 16.87 billion USD was in valuation of the AI market in 2024 and by 2030 the market will grow to 109.37 billion USD with a growth rate of 37.6 percent per annum from 2025 to 2030. The generative global generative market is estimated to reach 22.21 billion USD value in 2025, with projected values for the generative AI market increasing to 324.68 billion USD by 2033. The global generative AI market is expected to grow by 40.8 percent compound annual growth rate between 2026 and 2033 due to the adoption of generative AI technologies by multiple industries and the need for organizations to have modern workflows which these new AI apps will produce. Over years it has changed the way teachers customize curricula and how university students handle their coursework (Serhii Uspenskyi, 2025). Recent data indicates that 58% of university faculty or learners incorporate AI in their everyday activities and educational settings as well (Generative AI Already Being Used in Majority of College Classrooms according to Instructors, in New Wiley Survey, 2023). Generative AI simplifies lesson planning by enabling creation of personalized resources suited to varied educational requirements for teachers (Chris et al., 2024). AI agents serve as aides optimizing administrative duties and classroom management (Apeanti et al., 2025). The AI Teaching Assistant assists educators by automating duties such, as scheduling and tracking attendance greatly lessening their burden. Additionally the AI Grader enables educators to automate evaluation providing prompt feedback and freeing time for more individualized student engagement. To make learning more amusing, AI Gamification incorporates games that offer various levels of difficulty and prizes. This will increase their enthusiasm towards the learning process, resulting in increased achievement.

Figure 1.3

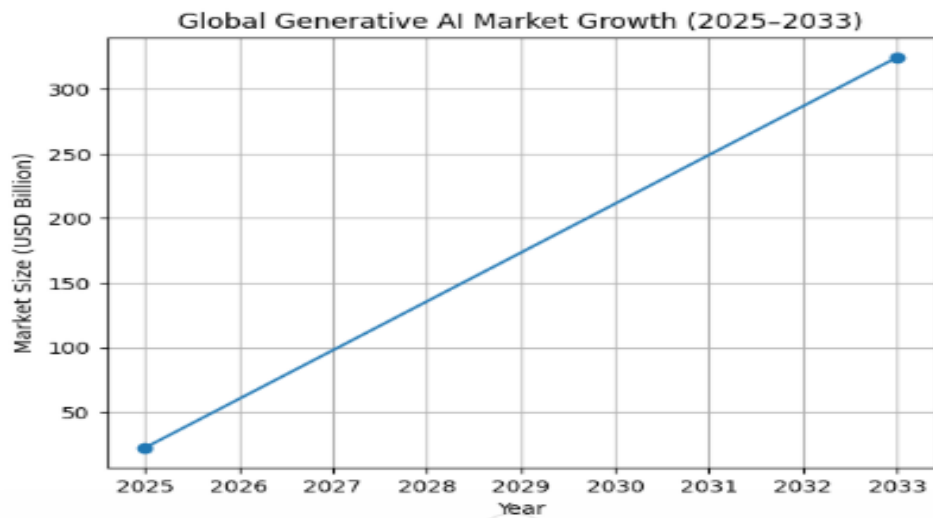
Projected Global Generative AI Market Size from 2024 to 2030



Note. Data from Generative AI Market Size, Growth & Share Report, 2030.

Figure 1.4

Global Generative AI Market Size from 2025 to 2033



Note. The world stage saw this technology grow its presence and use by almost 15 times during the eight-year period. The increasing importance of AI-driven technologies in enhancing efficiency and innovation in various

sectors of operation, however, is reflected in both trends. Data from Generative AI Market Size, Growth & Share Report, 2030.

Then, there is emerging work in collaborative AI learning, which is becoming very trendy with AI-facilitated group projects and peer learning initiatives (Kovari, 2025). Naturally, it is a research and design project aimed at utilizing innovative AI tools within a learning setting to facilitate learning in a collaborative group setting (Collaborative AI for Learning (CAIL), 2024). Students can now chat with AI during group projects and class stuff. This helps them work as a team (AI-Enhanced Collaborative Learning: Boosting Teamwork in the Digital Age- ILeaf Solutions, 2024). The idea is to have this AI chat partner push students to think a bit harder about the topics rather than just being a time-saver. Places that have started using AI collaboration tools have seen student project completion rates shoot up 40% with students getting more involved, it is no surprise that more and more solutions are being built for schools to help with teamwork (LAPU Digital Learning Solutions started rolling out their DLS in 2025). Now students can submit the AI's original suggestions along with their own editable version of the work and a reflection on how they made the changes (Posorski, 2025). And to put the nail in the coffin on relying too heavily on AI, teachers are requiring students to back up their changes with sources, this way potential cheating becomes a valuable chance to learn about the importance of human oversight and the limitations of AI. We also see a lot of value in activities where students compare multiple AI-generated answers to the same question, deciding which one is most suitable and why. This whole approach lets students evaluate the genuine value of AI, see where it falls short and where it makes mistakes, and why we still need humans to keep an eye on things (Usher, 2025).

Students can also get a lot out of pitting 3 different AI tools against each other by asking them the same question and then looking at how they answer. It is a great way to teach students how to evaluate different sources, spot any mistakes

and even figure out where they might need to dig deeper with some real research (Muhammad Dimas Rinjani Fitra et al., 2025).

1.1.4 Challenges of Artificial Intelligence in Education

The application of AI in education in particular, tools like ChatGPT has some pretty serious challenges that have got to be sorted out before it can be done properly. This section gets into some of the key problems that come up when trying to integrate AI into education, such as getting it to work for everyone, making sure students data is secure from prying eyes, and fixing some of the potential biases there are in how AI makes decisions.

One of the main headaches when trying to use AI in the classroom is making sure all students have a fair shot at using the AI-powered tools and resources that are available to them, regardless of where they are from or how much money their family has (Vesna, 2025). On the one hand, AI has got the potential to really take learning to the next level and help teachers tailor their instruction to individual students but the thing is, not all students have an equal chance at getting to the tech they need to make it happen. The students from less affluent backgrounds will face difficulties because they lack access to essential AI tools which include devices and software and internet connectivity. Students with disabilities will face difficulties using AI technology because the technology developers failed to address their specific requirements. This situation will make the technology divide worse between students who possess technological resources and students who lack these resources (Božić & Johansson et al. 2023, 2020). The team needs to work together with teachers and government officials and technology developers to create accessible artificial intelligence systems that will help solve present accessibility problems. This involves considerations for cost, ease of access, and the ability for platforms to interface with assistive

technologies. Plus, teachers and students need training to get started (Laxminarayana Korada et al., 2024). When schools use AI, they gather and handle a lot of student info, which raises some big privacy and safety worries (Jose, 2024). Schools and tech companies must follow tons of rules when they collect, use, and share student info. On top of that, they need to obey data protection laws, like FERPA in the US (U.S. Department of Education, 2011).

The use of AI in schools therefore presents a real challenge in keeping students' data private and safe (Samsudin et al., 2024). More AI learning platforms and data tools mean a greater chance of data leaks, unauthorized access, and misuse of student info by bad guys (Eden et al., 2024). AI needs lots of personal info to work well, but that makes data leaks even riskier. This could cause identity theft, cheating, and exposure of private info (Kotsis and Kundu, 2025,2024). Schools must establish effective data protection measures to address their concerns about data privacy and security. The system must implement multiple security measures which include encryption and access controls together with periodic security assessments to protect student information from unauthorized access and cyber threats (Almarroof Mariam Temidayo & Stephen and Education Cybersecurity for Safe Learning | EIRE Systems, 2025,2023). The process of collecting student data requires organizations to establish transparent methods which require obtaining consent from both students and their families. Then, they can decide whether to allow its collection and sharing (Jerome and Rosângela Miranda Cremonini et al., 2014,2025).

One big problem with using AI in education is that AI programs can have biases. This can make things unfair and not work as well as they should (Boateng & Boateng, 2025). AI biases can come from a few places. Sometimes, the info used to train the AI is biased. Other times, it is how the AI is designed. Sometimes, this is because such information has societal prejudices embedded in it (Hanna et al., 2024). The data which AI uses for learning contains biases which become part of its system. The system will continue to show bias against students

because it uses outdated materials which provide advantages to certain groups (Hanna et al., 2024). If we don't get how the AI decides things, it is hard to fix these biases (Crespo, 2022). To fix this, teachers and tech experts should be fair and open when they create and use AI (Xivuri & Twinomurinzi, 2023). Check the info the AI learns from, use special AI to cut down on bias, and regularly test the AI to be sure it is not hurting some students (Yurt, 2024). Tech people could also make a list of approved AI tools and tell staff and students the rules. Teachers require assistance with learning about the System and the Associated Guidelines. The current guidelines require updates because artificial intelligence develops quickly and technological progress creates more complex challenges (British Council, 2024).

1.2 Research Problem

It is still a long way before substantial influence of AI on students' education and lifestyle is to be studied fully, the case being that this technology is already capable of making a drastic change in the way students learn and behave, it can be criticised for not tackling the issue genuinely, as the impact is much more profound (Slimi, 2023). Indeed, focusing on the learning and teaching process, no one would doubt that AI is replacing the lecturer or tutor in many ways, such as blended learning and e-learning. The student body is turning to AI tools for various purposes which include coming up with ideas, giving concise readings, doing written assignments, and perfecting their conversations with peers and professors. However, the presence of an e-learning lecturer is limited as the learner interacts with a virtual classroom, such as Moodle (Saleh, 2020). The use of these technologies by students can bring along huge advantages, both personally and academically, but at the same time, there is a common dilemma concerning the necessity of digital literacy skills, usefulness and convenience of AI and social influence.

While there is an increasing investigation into AI and adoption of AI into the educational experience, most students will likely not possess digital literacy in order to critically examine or be totally constructive in learning with an AI tool. The acceptance of AI tools by students would highly depend on their perceived usefulness and ease of use, as dictated by the Technology Acceptance Model. Whereby some students find AI applications helpful and efficient, others may perceive them as complex or unreliable, since it affects their motivation in using the same tools and their integration into learning routines. Further, their attitudes toward AI, as led by the Theory of Planned Behavior, will determine whether they view it as a legitimate aid or a threat to academic integrity.

1.3 Research Objectives and Research Questions

1.3.1 Research Questions

1. What is the impact of digital literacy on students' learning efficiency concerning the use of AI?
2. How does the perceived usefulness of AI impact student learning efficiency?
3. What is the impact of the perceived convenience of AI on the students' learning efficiency?
- 4.. How do social attitudes towards AI impact students' learning efficiency?

5. How does the intention to use AI moderate the relationship between dependent and independent variables?

1.3.2 General Objectives

The ultimate goal is to analyse the multifaceted impact on students' learning efficiency through the use of AI, like ChatGPT.

1.3.3 Specific Objectives

1. To evaluate the impact of digital literacy on students' learning efficiency when using AI tools.
2. To determine the influence of the perceived usefulness of AI on students' learning efficiency.
3. To disseminate the impact of the perceived convenience of AI on students' learning efficiency.
4. To determine the impact of social attitudes towards AI on students' learning efficiency.
5. To evaluate if the intention to use AI positively or negatively moderates the relationship between independent variables (Digital Literacy, Perceived usefulness, Convenience and Social Influence) and the dependent variable (students' learning efficiency).

1.4 Research Significance

“AI is already shaping the future of education in ways that everyone in the sector, from policymakers and leaders to teachers, parents, and students, needs to understand,” Martin West said. The research will present descriptive statistics on the student behaviours, predict the theoretical processes including TAM predictors of adoption to generate practical suggestions that teachers or educators can use to incorporate AI into the learning processes without compromising learning integrity (Mustofa et al and Sun et al., 2025). Besides that, AI can support education by automating administrative tasks, freeing teachers to focus more on teaching and personalized interactions with students, enhancing rather than replacing human-led teaching (Milberg, 2024).

The study is relevant to the existing field of research in educational technology since it offers a broad framework of understanding the effects of AI on learning (Naseri & Abdullah, 2024). AI builds on the knowledge of technology-enhanced learning and provides new insights on the human-AI interaction during learning. It can tailor the learning experience to the individual, enhancing academic performance while seamlessly catering to diverse learning needs (Southern Methodist University, 2025). To the students, it will provide an evidence-based introspection of their own actions and will help them to develop more aware and purposeful approaches to using AI to support their learning processes and not to burden them (Cardona et al., 2023).

The results will guide the process of policy formulation, curriculum design and instruction. The study offers evidence-based insights to education, administration, and policymakers that would want to implement AI tools in a manner that is effective, and the potential risks are reduced (Umoke et al., 2025). The findings will be useful to educators and institutions because they can guide the reconstruction of curriculum, design new assessment approaches, and elaborate on the new clear and practical

academic integrity policies that are specific to the AI age (Liat Eyal & Nehemia Ronit, 2025). The study will be also useful to policymakers as it will add to the overall discussion about the role of AI in national education policies and the requirement to implement digital literacy programs and ethical principles (Artificial Intelligence and Education. Guidance for Policy-Makers, 2021). AI developers will acquire knowledge about user experiences and user challenges because this information will help them create ethical and educational AI development solutions (Temini et al., 2025).

1.5 Conclusion

Chapter 1 was used to outline the rationale and context of the study, as AI in education is disruptive and transformative, placing the research within present trends and gaps. It has presented the essence of research problem, explained the research questions and objectives and emphasized the importance of the research under study. The following chapter will discuss background theories and the empirical evidence that will inform the conceptual framework and research hypotheses of the current study.

CHAPTER 2: LITERATURE REVIEW

2.0 Introduction

This section portrays past literature about the influence of using artificial intelligence (AI) on the learning processes of students in the present times. Relevant information was taken from past literature to review the matter regarding the impacts of using ChatGPT on the learning of students. Enhancing students' performance in their academic field with the aid of accessible learning materials and resources is a vital implication of ChatGPT. This section highlights different variables connected with the topic of this study. On account of associated variables, past literature is considered to assess various variables to understand the study topic. Implications of digital literature on the students' intention of using AI and its influence on their learning are mentioned. Positive perception of students regarding the effectiveness of ChatGPT for boosting their learning outcomes influence students to adopt this AI-driven technology. This chapter showcases how social influence and the convenience of using technologies influence students to adopt AI to elevate their learning efficiency. This is the basis to answer the question of what factors influence the use of ChatGPT in learning by students. This study can understand psychological factors such as social influence in accepting the use of new technology. Theories congruous with this study topic to spotlight the effects of AI that is part of everyday life on learning outcomes for students are mentioned. Hypotheses based on variables of this study are formulated in this chapter. The research framework is developed in this study, illustrating the relationships between independent, moderating and dependent variables.

2.1 Underlying Theory

This study's purpose on AI's impact on students is to understand how these AI tools affect learning outcomes for students.

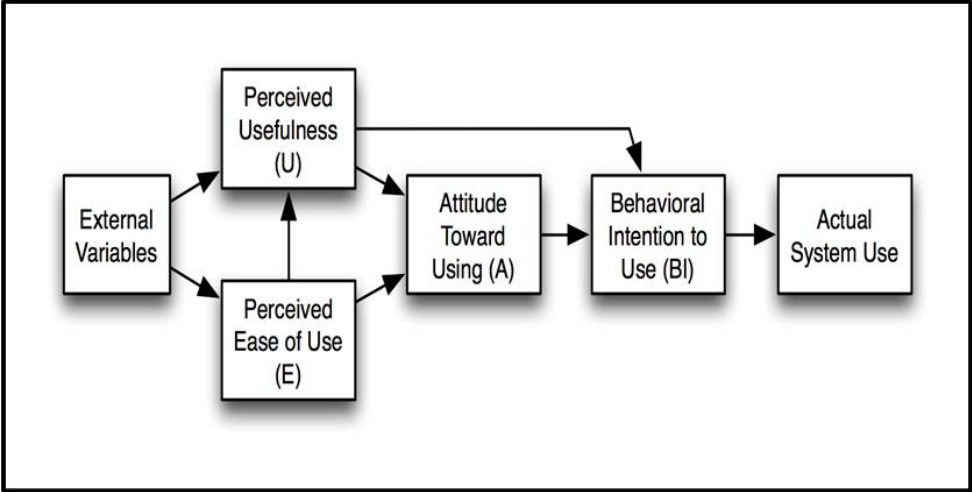
2.1.1 Technology Acceptance Model (TAM)

Embracing AI in learning methods of students is interconnected with positive attitudes towards technology acceptance. With respect to applying TAM, students are influenced to enlist AI-powered ChatGPT in their learning processes to elevate efficiency in learning. As investigated by Mailizar et al. (2021), influencing behavioural aspiration of students is a paramount matter in the context of TAM and its associated components, which amplify positive perception of students about enlisting technologies. In connection of the application of TAM, students' attitudes towards enlisting AI-driven ChatGPT is affected to refine their learning efficiencies.

Wang et al. (2021) mentioned that ascertaining students' attitudes towards endorsing AI in learning methods is controlled by perceived usefulness. With the aid of perceived usefulness students' perception about using AI in learning is determined. In the matter of embedding AI in daily lives, influencing students' attitudes is consequential for raising adoption of this technology. Through revamping positive perception among students about using a specific technology, their intention towards its adoption is controlled. As stated by Alshammari & Babu, (2025), determining students' intention towards endorsing AI-based technologies in learning procedures is controlled by perceived ease-of-use. In the connection of this factor, students' belief about

ease of using a certain technology ascertain their intent to appraise technology for elevating learning outcomes.

Figure 2.1
Components of the model of technology acceptance



Note. Reprinted from “Examining Teachers’ Behavioral Intention to Use E-learning in Teaching of Mathematics: An Extended TAM Model” by Mailizar et al, 2021, Mathematics Education Department, Universitas Syiah Kuala, Indonesia.

As highlighted by Belda-Medina & Kokošková (2024), perceived usefulness in the thinking of ChatGPT is an indicator to students of their perceptions that AI facilitates their learning efficiency, helps them acquire intricate concepts more rapidly, better academic performance, and reduces the challenges encountered daily in studying. In the meantime, the perceived ease of use looks at the intuitive, accessible, and easy-to-use nature of the AI interface, as perceived by students. The reason for using TAM in this study is to identify how such perceptions define the attitudinal and intentionality of students about the use of AI. The simplicity of the model and its empirical power have rendered it an important instrument to establish the key psychological elements that forecast

adoption. Through the application of TA, the research will be able to find out whether the common use of AI by students is motivated by the perceived benefits or their convenience (Sallam et al. 2023). It assists in achieving the recognition of the disparities between students with varying levels of digital literacy or technological experience, and teachers could get to know more about how to improve the learning environment through AI.

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

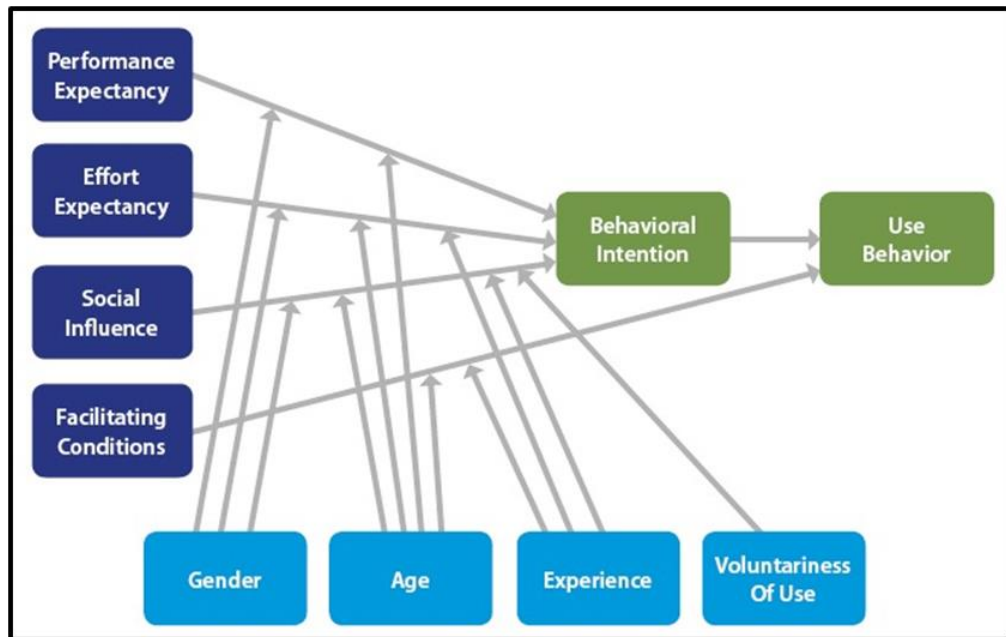
In the matter of understanding the willingness of students to encompass new learning tools, application of UTAT is functional. This theory consists of four elements which are imperative to influencing the minds of individuals regarding technology acceptance (Aldhaheeri & Ishak, 2025). Motivating willingness of students to enlist AI-driven tools positively affect their intention to adopt AI for reinforcing their learning. This factor of motivation is paramount to embrace ChatGPT by students to revamp learning outcomes. with the aid of the element “Performance expectancy” in UTAUT, belief of students regarding positive consequences of AI-driven learning technology is ascertained. By means of influencing of this component, students enlist ChatGPT which provides them with personalised learning experiences.

A factor of motivation for students is “Effort expectancy”, impacts their belief regarding ease of use in the matter of ChatGPT. Appraising the intention of students to append new technologies in their learning depends on ease of use. Bin-Nashwan et al. (2023) opined that by means of positive social influence, students’ belief that learning technology is fcuntional for nurturing tehri learning efficiency. With the aid of “social influence” in UTAUT, students’ intention to adopt ChatGPT is ascertained for uplifting their efficiency in

learning. Offering technical support along with conducive resources is paramount for students to adopt AI for accelerating their learning outcomes. On account of “Facilitating Conditions” in the UTAUT, requisite resources and infrastructure are provided to students for embracing learning technologies (Bayaga & du Plessis, 2024). It is remarkable to assure availability of compatible infrastructure and support for students to drive their willingness towards appraising AI to boost their learning outcomes.

Figure 2.2

Imperative component in UTAUT



Note. This figure was created by the author Chin Yin Tong. Data from Use of ChatGPT in academia: Academic integrity hangs in the balance by Bin-Nashwan et al, 2023.

The Unified Theory of Acceptance and Use of Technology (UTAUT) is based on the analysis and puts into consideration the social and contextual factors. Some of the variables available in UTAUT include performance expectancy,

effort expectancy, social influence and facilitating conditions, and they play an important role in the implementation of AI in learning institutions. According to Budhathoki et al. (2024), the opinion of students regarding whether the use of AI tools such as ChatGPT really improves their academic outcomes, research productivity, or time-saving can be determined through the performance expectancy. The theme of easy to use applies to the concept of effort expectancy but in a broader context. The social influence is particularly significant since students are strongly influenced by other students, teachers, and academic norms, among other spheres that have a strong impact on the decision-making regarding AI use. Facilitating conditions look at external enablers like the policies of the institutions, the availability of the internet, the availability of the devices, and ethical guidelines. As highlighted by Strzelecki (2024), the advantages of UTAUT application to the research are that it generates an overall and realistic perspective that crosses over individual beliefs. It increases awareness concerning environmental barriers which may prevent the implementation of AI, illustrates how peer culture may affect the level of acceptance and increases the predictive validity of behaviour.

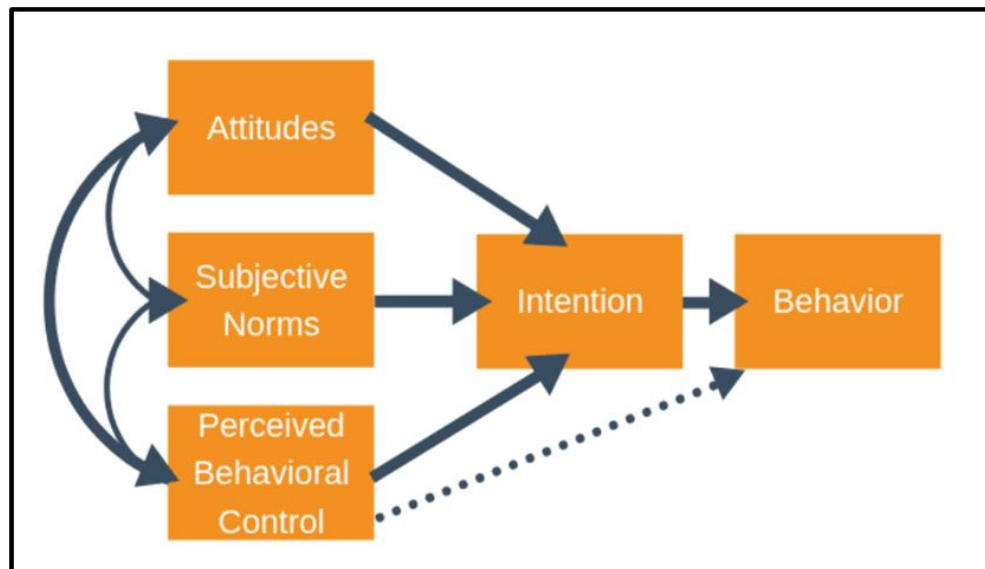
2.1.3 Theory of Planned Behaviour (TPB)

Controlling students' intent towards endorsing a specific technology is determined by their behaviour. In the connection of executing TPB, attitudes of students towards endorsing AI-based technologies is appraised (Wang et al. 2025). By means of integrating this theory, students are encouraged to enlist ChatGPT to positively control their learning procedures. In the connection of applying this theory, students' attitudes, along with subjective norms, and behavioural control are determined to affect their intention to execute AI.

As mentioned by Le et al. (2022), assessing students' behaviour about enlisting technologies in their learning methods is crucial in the connection of executing this theory. In case of integrating TPB and associated elements, subjective norms and others' influence are requisite for controlling students' intention. These elements are imperative for students to guide them in embracing ChatGPT for revamping their learning outcomes. With the aid of positive feelings and confidence of students with respect to encompassing AI-based technology in learning, their behaviour is determined. Assimilating the component of perceived control of behaviour is paramount for controlling the intention of individuals towards embracing technologies (Al-Mamary et al. 2024). In the connection of applying TPB as well as its components, intention of students regarding embracing ChatGPT in their learning processes is guided to nurture their learning efficiency.

Figure 2.3

Key elements in TPB



Note. This figure was created by the author Chin Yin Tong. Data from Investigating Chinese English learners' readiness for Artificial Intelligence (AI) technologies: A theory of planned behavior (TPB) perspective. Learning and Motivation, 91, 102164–102164 by Zhang, 2025.

As proposed by TPB, attitude, subjective norms, and behavioural control perceptions influence the behaviour. With reference to AI tools, the attitude will be employed to assess the positive or negative orientation of the students to use ChatGPT to learn, to be creative, and to work on assignments (Ahadzadeh et al. 2024). Subjective norms examine the role of peer pressure, where other students are urging students to use the AI, where the teacher is telling students that students should avoid overuse, or where the school or college is urging students to be responsible in integrating AI. Measuring perceived behavioural control evaluates the confidence of the students to use AI in a responsible manner and handle the problem of academic integrity. As illustrated by Haq et al. (2025), the advantage of using TPB is that it can help to reveal psychological and ethical justifications of using AI. TPB provides the reasons why perceived risks, moral considerations, and self-control influence the intentions and actual behaviours of students.

2.2 Concepts of Variables

2.2.1 Independent Variable: Digital Literacy

Having digital literacy is paramount for students to handle digital educational resources, which support them in their learning processes. Cultivating technical abilities as well as cognitive skills is imperative for students to operate modern devices and perform safe online behaviour. Prasetyo et al. (2023) investigated that the digital literacy of students is interrelated with their skills of digital citizenship, which assist students in performing responsible behaviour while browsing online sites. With the aid of digital literacy, students could participate

in online courses to elevate their learning outcomes as well as academic performance. Bucăța & Tileagă, (2024) highlighted that revamping the proficiency of students to handle digital educational tools is functional for progressing their future careers through their engagement in international discussions. By dint of digital literacy, students are encouraged to adopt AI-powered educational tools like ChatGPT to drive their access to learning resources.

Uplifting the proficiency of students to tackle digital technologies for browsing online educational sites is vital for expanding their academic success. Silvhiany et al. (2021) opined that raising the critical thinking ability of students to investigate online educational information from reliable sources is a vital aspect of digital literacy. With the assistance of digital literacy, students might make decisions regarding exploring online information from credible sites by means of avoiding the risks of biases. Yu (2022) highlighted that developing digital literacy is indispensable for students to communicate with their peers, along with teachers, through online sites to drive learning outcomes. Elevating the required knowledge of students to tackle AI-based tools is a functional aspect of digital literacy, which positively impacts the intention to encompass modern educational technology. Conversely, Delello et al. (2025) stated that with the support of digital literacy, students use AI-based educational tools to perform their learning processes, which reduces in-person communication among students and results in social isolation. Excessive dependency of students on ChatGPT, with the support of digital literacy for performing their learning activities, causes the issue of cursory learning.

Digital literacy serves as an essential requirement for fostering ethical behavior within academic settings. The growing digital skills of students require them to learn ethical principles for dealing with plagiarism and copyright violations. Students tend to commit plagiarism and copyright violations because they have easy access to information (Sharil et al., 2025). Digital literacy needs to expand

past basic technical skills for information access to include ethical standards for using accurate information. As such, digital literacy should extend beyond the technical coping skills to access information to include the ethics of accessing the correct information.

2.2.2 Independent Variable: Perceived Usefulness

Influencing the intention of students to encompass AI-driven educational tools is a vital aspect of the perceived usefulness concept. With the aid of this concept, the beliefs of students about the positive outcomes of using AI-enabled educational tools are contemplated. Badr et al. (2024) opined that the faith of students in interactive educational technologies, which could boost their learning outcomes and academic performance, is associated with perceived usefulness. With the credence of students that ChatGPT might elevate their learning outcomes and academic success, they are encouraged to adopt this tool to influence their educational procedures. As per the opinion of Alyoussef & Omer, (2023), a subjective trust of students is associated with the perceived usefulness of specific technologies, which might uplift their efficiency in learning processes. By dint of this subjective faith, students are inspired to enlist these technologies to bring changes in their learning processes with the purpose of gaining success in the academic field.

Making activities efficient and faster is one inescapable impact of the belief associated with the perceived usefulness of the AI-driven tool ChatGPT for students. Kong & Wang, (2021) highlighted that the perceived usefulness of a specific educational tool motivates students to use these tools to drive positive consequences in learning. The belief about using a specific system could nurture the overall effectiveness of learning processes encourage students to be engaged in learning activities. Soliman et al. (2025) mentioned that engaging

students in learning materials which are available in AI-driven tools is an indispensable consequence of perceived usefulness. In the matter of encouraging students to adopt particular technologies or digital tools to revamp their learning outcomes, the factor of perceived usefulness is remarkable. This factor of subjective faith in certain tools or digital educational resources is linked with a positive perception of students. Liesa-Orús et al. (2023) stated that a positive perception of humans is interlinked with perceived usefulness, which increases positive attitudes toward encompassing certain tools to make their activities easy. On the subject of embedding AI-driven educational technology, the positive perception of students about the fruitfulness of ChatGPT is notable for boosting their positive attitudes towards elevating academic success.

2.2.3 Independent Variable: Convenience and Social Influence

There is an intricate relationship between social influence and convenience. Formulating a behaviour or using certain items is magnified or disheartened by seeing the activities of others. Influencing decisions of students regarding encompassing AI-based educational tools is amplified by the behaviour of others. Kim et al. (2021) investigated that the factor interconnected with social influence provides an indication to students of the way of acting with respect to using interactive educational tools. Encouraging students to engage in digital educational procedures to elevate their learning outcomes is a profound aspect linked with social influence. Formulating a normative belief of students to be engaged in certain behaviour in the matter of their learning processes is impacted by social influence (Veenstra & Lodder, 2022). Teachers play a key role; for instance, if teachers use AI in class and get students to try AI for problem-solving, students will probably be more open to using AI (Yahaya Nasidi et al., 2025). Also, getting hints of adopting certain technologies by students is impacted by social influence, which is interrelated with the use of

those technologies by others. By dint of positive social influence, positive attitudes of students towards encompassing AI-driven educational tools are fostered, which has a positive consequence on using ChatGPT to nurture learning outcomes.

Impacting the perception of students to enlist certain educational tools is accompanied by the convenience of those tools. Bansah & Darko Agyei, (2022) mentioned that the convenience of educational technologies supports students in accessing resources and completing their learning activities in an easy way. With the assistance of these factors, intertwined with the convenience of AI-based educational tools, generate a positive perception of students towards encompassing these tools. Shifting the methods of learning from traditional processes to technology-driven procedures is affected by the convenience of specific educational tools (Sharma et al. 2024). With the support of convenient technology, students might revamp their positive perception towards executing the technology to boost the outcome of their learning. The factor, convenience, is connected with the dependency of students on AI-enabled educational tools to strengthen academic performance.

2.2.4 Moderating Variable: Intention to Use AI

Constructing the assent of individuals to encompass AI-driven tools to make their daily activities efficient is depicted through the variable of intention. This factor is impacted by the positive perception and attitudes of students towards enlisting AI-powered tools. As depicted by Purnama et al. (2023), with the support of a positive perception of students about the consequences of embedding AI-enabled educational tools, their desire of executing these tools to promote learning outcomes is nurtured. By means of a positive faith of students in the profound remarkability of ChatGPT in the context of their

learning efficiency, the motive to incorporate this tool is magnified. From the viewpoint of Zaman et al. (2025), it is understood that positive social influence is a consequential factor in the matter of generating the assent of students to incorporate an AI-based tool in their learning processes. With the support of a pleasure-seeking attitude of students, which is connected with their motivation for executing AI-driven educational tools, is paramount in formulating the motive of students.

Nurturing the assent of students with respect to AI-driven tools adoption is interlinked with their intention, which fosters overall learning performance. Imamguluyev et al. (2024) assessed that the ability of students in the matter of handling modern educational tools is a noteworthy aspect of creating their desire to encompass AI-driven tools. With the assistance of digital literacy, ethical online behaviour, along with the critical thinking ability of students, is promoted to positively impact their motive to execute ChatGPT. The factor, students' desire to integrate AI-enabled learning processes, is affected by their positive attitudes and the convenience of these processes (Lin & Chen, 2024). Boosting the willingness of students to incorporate an AI-driven tool for cultivating their learning activities is connected with their amplified efficiency in learning.

2.2.5 Dependent Variable: Students' Learning Efficiency

Discovering knowledge in a little time and retaining the knowledge for a longer time to progress in academic performance is the learning efficiency of students. With the aid of learning efficiency, students might revamp their academic performance through a high level of retention ability (Hooda et al. 2022). Practising learning activities in a conducive way, along with establishing comprehensive plans for study, is functional for driving the efficiency of

students in learning procedures. Qadir et al. (2024) opined that methods of learning are conducive factors in the context of elevating the efficiency of students in their learning to uplift the entire performance in academic fields. With the assistance of AI-driven educational tools, students might revamp their ability in learning with respect to accessible learning resources. Javaid et al. (2023) mentioned that offering a personalised learning process is a paramount aspect of ChatGPT, which boosts the proficiency of students in critical thinking to elevate the overall efficiency in learning. On account of students' engagement with the ChatGPT tool, accessible learning materials are imperative for students to nurture their proficiency in learning.

Enhancing the performance of students in their academic field, along with progressing their future careers, is connected with learning efficiency. Bai et al. (2023) investigated that efficient students could gain knowledge easily from learning resources and retain the knowledge for a longer period, which results in better academic outcomes. ChatGPT decreases unnecessary mental effort which people need to collect information and helps students by making it easier to produce summary content from large data sources which enables them to use their mental capacity for advanced critical thinking and analytical skills. The shift allows students to concentrate on understanding core concepts instead of struggling with the process of finding information which results in better retention of knowledge (Ragab et al., 2025). On the subject of revamping the efficiency of students in learning, AI-based learning tools are paramount. With respect to adopting AI-driven learning tools, ChatGPT impact on the proficiency of students in learning activities. Driving the positive attitudes of students towards encompassing this AI-enabled educational technology is crucial for incorporating this tool to amplify the ability of students in learning (Strielkowski et al. 2025). With the assistance of the positive perception of students about the AI-powered learning tool, ChatGPT, students embed this tool to magnify their academic performance through efficient learning processes.

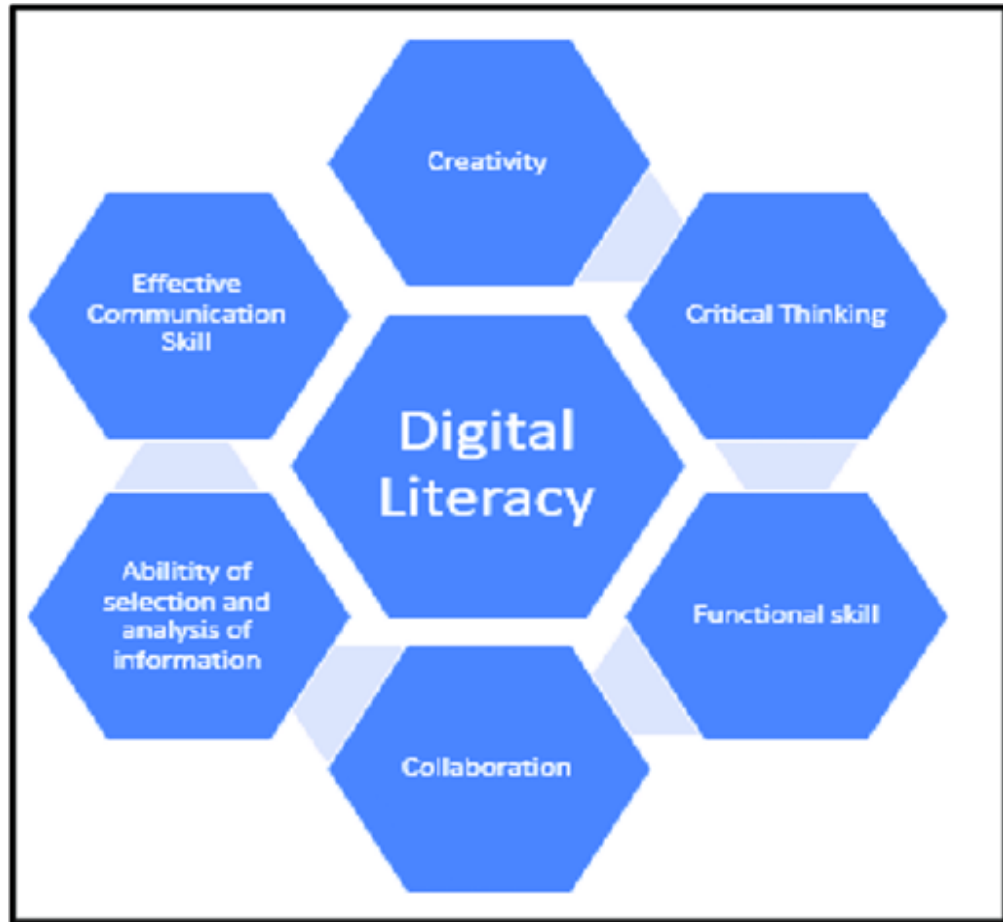
2.3 Review of Variables

2.3.1 Influence of digital literacy of students on their learning efficiency through embracing AI

Driving digital literacy of students is consequential for influencing their intention to incorporate ChatGPT in their learning activities. As per the opinion of Scheel et al. (2022) presence of notable digital skills in students is indispensable for developing their intention to adopt new learning technologies through confidence. On account of academic pursuits, students who have digital skills and associated literacy have more confidence to encompass evolving technology to elevate their learning experiences. With the aid of digital literacy, students become capable of searching for information and assimilating learning resources from online sources through handling digital tools in an efficient way. Through their complete mastery of digital tools, students gain the ability to create educational materials which match their personal learning preferences and study speed thus achieving their educational goals according to their unique needs. Eden et al. (2024) mentioned that adapting to the modern learning environment is consequential for students to boost their academic performance and capability in learning activities. On account of accelerating digital literacy and interlinked skills, students of contemporary learning systems could adapt to the modern academic environment to learn through blended courses. Yu (2022) opined that students boost their digital literacy because this component is functional for allowing students to handle learning technologies and adapt to modern instructional methods. With the aid of digital literacy, confidence of students, along with their technology handling abilities, is increased to positively impact their intention towards adopting AI.

Figure 2.4:

Key skills associated with digital literacy



Note. This figure was created by the author Chin Yin Tong. Data from_The influence of digital competences, self-organization, and independent learning abilities on students' acceptance of digital learning by Scheel et al, 2022, International Journal of Educational Technology in Higher Education 19(1).

Revamping the digital literacy of students is remarkable for elevating their digital skills, which results in improved management capabilities of students to embrace learning tools. Mhlongo et al. (2023) investigated that with the aid of conducive digital skills, students could handle learning tools and engage in personalised learning processes to refine their learning experiences. By means

of conducive digital literacy, students might increase their ability to collaborate in the learning environment with interactive tools. Comprehensive digital literacy of students is crucial for engaging them in ChatGPT to gain experience of personalised learning, which boosts their learning outcomes. Khan et al. (2022) assessed that driving digital literacy is linked with better performance of students in their academic field because of revamping their skills to manage digital learning. Reinforcing confidence of students and their digital skills is functional for guiding their behaviour of adaptation in the digital learning environment. With the aid of digital literacy, students' intention is governed to endorse ChatGPT in learning.

Cultivating the process of self-regulated learning is an ineliminable aspect of digital literacy, which supports students in grasping digital education tools to nurture the consequences of learning. By means of the method of self-regulated learning, students might be capable of managing their learning through conducive planning and evaluation to accomplish academic objectives. As assessed by Karlen & Hertel, (2024), nurturing students' inspiration in learning, along with engaging them in learning activities, is the profound consequence of self-regulated learning. With the aid of digital literacy among students, the method of self-regulated learning is strengthened, which results in amplified academic outcomes. The assent of students to encompass the AI-driven educational tool, ChatGPT, is intertwined with digital literacy, which enriches the learning efficiency of students. Getenet et al. (2024) mentioned that increasing the aspects of digital literacy is consequential for students to revamp their technological self-efficacy (TSE), which supports them in endorsing interactive learning tools.

Enriching the components connected with TSE is functional for students to drive their capability of executing AI-driven educational tools to achieve learning goals. With respect to the increased TSE, students become encouraged to boost their desire to embrace AI-based ChatGPT to amplify their learning

outcomes. Students' autonomy in their learning procedures is intricately linked with digital literacy, which assists them in managing learning procedures independently. Zeng (2023) investigated that intensifying autonomy of students in their learning methods is functional for strengthening their engagement in learning with the support of digital literacy. Enriching the digital skills of students is paramount for amplifying their desire to execute AI-powered tools to boost autonomy in learning, along with progressive academic performance.

2.3.2 Discussion about perceived usefulness in the context of embracing AI for cultivating learning efficiency of students

Emphasizing the perceived usefulness of AI-driven learning tools is functional to understand the intention of students to adopt modern learning technologies. With the aid of a positive perception regarding using ChatGPT, students might boost their intention to embrace this evolving technology to elevate their learning experiences. Soliman et al. (2025) investigated that considering AI-powered learning tools as valuable for revamping learning outcomes, students pursue their intention to adopt AI in their learning processes. Providing personalised learning experiences is a crucial usefulness of AI-based learning technology, specifically ChatGPT. With the increasing rate of positive perception regarding personalised learning through AI-driven technologies, students' intention is fortified to embrace this tool. Anjum et al. (2024) opined that offering a personalised experience of learning is a positive aspect of using the ChatGPT tool, which results in increased students' motivation in learning. By dint of positive perception about the usage of AI-driven learning tools among students impacts their intent to encompass the tool to fortify their learning outcomes. Qazi et al. (2024) assessed that AI-driven learning tools, especially ChatGPT, offer 24*7 on-demand support to students through their potential for accessibility to learning resources. Accessing learning materials as

per the needs of students is consequential for meeting diverse learning needs, which results in positive academic performance. Offering assistance to students in their learning activities is a usefulness of an AI-driven learning tool; the perception of students about this support of AI boosts their intent to integrate learning technology to revamp their efficiency.

Cultivating positive perceptions and attitudes of students towards adopting ChatGPT is inevitable to boost their willingness to invest in this tool. Valverde-Berrocoso et al. (2022) stated that the belief of students about positive academic performance with the aid of certain technology influences their willingness to invest in those tools. On account of the increased willingness of students to adopt AI-driven learning tools, their belief in positive academic performance is remarkable. Promoting positive attitudes of students towards embracing ChatGPT in their learning processes is impacted by their positive perception of the effectiveness of AI-powered learning tools (Dahri et al. 2024). With the aid of the perceived usefulness of ChatGPT usage among students, the barriers to transforming traditional learning processes could be eliminated. Driving the perception of students about the enhancement of their learning efficiency by dint of ChatGPT is paramount to elevate their intent to adopt this tool.

Achieving academic objectives is an ineliminable aspect of students in their learning processes; this aspect is linked with a positive perception of students about endorsing AI- based educational tools. Al-Abri (2025) mentioned that providing adequate support to students in completing their homework and preparing them for examinations is an imperative aspect of ChatGPT, which assists students in accomplishing academic objectives. In the matter of embracing AI-driven learning tools, positive attitudes towards those tools are paramount for students. The perception of students is intricated with the positive consequences of ChatGPT impact on their assents to incorporate this tool. Lee et al. (2024) opined that a flexible learning environment is offered to students while they endorse ChatGPT for performing their learning activities.

With the aid of a flexible procedure on account of executing ChatGPT, students could explore various topics and get bespoke support to enrich their proficiency in learning. The faith of students in these positive consequences of endorsing this AI-powered learning tool influences their desire to embrace ChatGPT to drive learning coherence.

2.3.3 Exploration of the effects of convenience and social influence on the intention of students towards using AI in their daily life and learning processes

Influencing the intent of students to embrace an AI-driven learning tool is interrelated with the matter of convenience. With the aid of the belief about the ease of use of certain technologies, students adopt those technologies to nurture their learning efficiency. Almaiah et al. (2022) mentioned that the convenience of using learning technologies is connected with their ease of use, which influences the willingness of students to encompass digital learning tools. With respect to the adoption of ChatGPT, the convenience of its assistance to students in getting feedback and summarizing information is imperative to fortify learning efficiency. The role of convenience is central as students today have to maneuver through hectic schedules, several deadlines, and excessive information loads. As highlighted by Ayanwale & Molefi (2024), artificial intelligence systems that make work easier, lighter, and faster are, of course, attractive. To a lot of students, the technology itself is not very appealing, but the ease in completing most of their daily tasks, whether it is writing explanations, clearing up concepts, creating examples, or even helping with language-related assignments. The importance of AI is demonstrated through its ability to provide fast and on-demand services that substitute time-wasting manual searching or other traditional ways of seeking help. Such effort-

reduction makes AI tools become a sort of academic shortcut, which, however, does not always undermine the learning process, but helps students to be more efficient in the way they process and arrange information. As per the view of Al-Abdullatif & Alsubaie (2024), a tool that fits into the rhythm of everyday life of a student, which can be accessed on a phone, is available at any hour of the day and can process various topics, becomes a part of it not only as an academic aid but also as an inherent attribute that can accompany them in their everyday activities. This smooth usability supports the idea that AI is not an extra tool but a complement to the current learning management approach and, therefore, the desire to use it regularly.

It is also relevant to convenience since students tend to perceive learning as a practice that should be made to suit personal tastes. Individualized clarifications, expedited corrections, or feedback that is not emotional assuage the fear commonly found in seeking clarification from the teacher or a colleague. With this feeling of self-determination and the instant satisfaction provided by AI, good attitudes are developed that foster the use of AI over time (Li, 2023). The convenience of AI is even greater to the students who lack support systems in some subjects or have lower requirements in specific subjects, since AI acts as a judgment-free tutor. Being able to receive individualized advice without the limitations of the appointment schedule or institutional access increases the attractiveness of the AI beyond academic brilliance to the customers who just want their day-to-day operations to be a bit easier.

In addition to convenience, social influence is a key factor that will determine the willingness of the students to implement AI. The decisions of the peers tend to influence norms and expectations in educational settings, as well as their view of legitimacy. As students will see peers with higher efficiency in applying the AI tools to do tasks or get more clarity in the assignments, they will see AI use as positive and socially acceptable (Sallam et al. 2024). Such an impression decreases the level of uncertainty and makes them want to explore AI

themselves. The introduction of AI in group chats, classroom work, and project work increases its visibility to make it not a necessary tool but a perceived academic support. Once learners start citing AI-created knowledge more often or when the teacher encourages brainstorming with the help of AI in group work, the fear of lagging becomes an insidious but steady influence.

Furthermore, a vital factor that affects the willingness of students to adopt ChatGPT is social influence. Al-Mughairi & Bhaskar, (2025) opined that cultivating social influence through peers' usage and advocacy of educators motivates students to embrace AI-driven learning tools. It is a paramount motivator for students to adopt ChatGPT when they see their friends or family members get benefits from this tool. With the aid of positive social norms, students become encouraged to appraise AI in a responsible way to reinforce their efficacy in learning (Wang et al. 2023). Motivational factors interrelated with social influence are functional for affecting the intent of students to adopt ChatGPT in their daily lives. On account of the influence of peers and families, students adopt this learning tool to revamp their academic outcomes through personalised learning and automated activities.

Besides, educators have a considerable impact on students who want to embrace AI. As soon as lecturers or tutors mention AI as a valid aid, be it idea generation, critical thinking training, or academic writing, students understand such recommendations to state that the technology is in accordance with academic norms. Through this advice, there is less fear of misuse, and the adoption is less fraught with fear and more academically sound. Online communities and digital platforms also introduce students to a wider culture of AI usage, where stories, guides, and recommendations made by peers make the use of AI normalized part of everyday life (Duong, 2024). The attitude towards AI can also be shaped by the family members (particularly, those who treasure the technological advancements or encourage the digital literacy within the family). As long as the students see how AI assists their siblings, parents, or friends in the office,

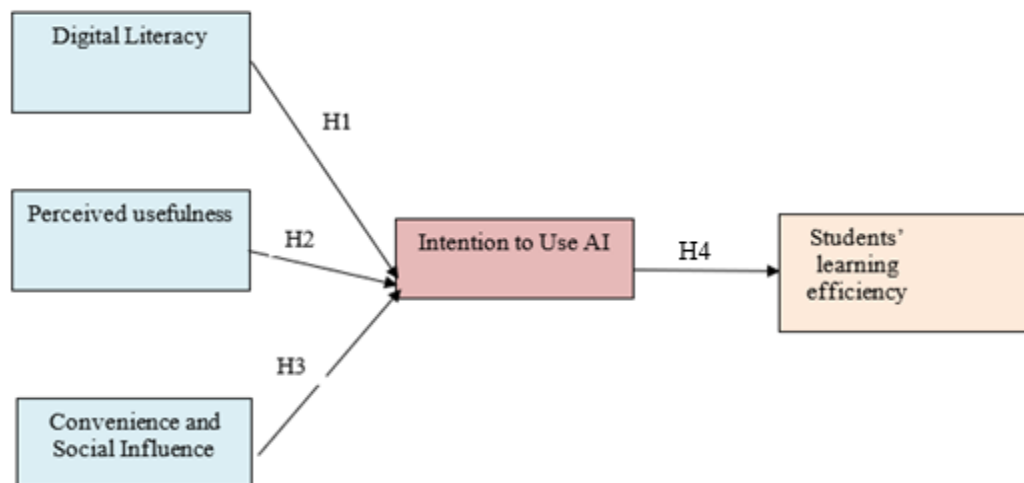
the perceived utility of AI is not restricted to the academic setting, but rather a life management in general, which justifies the long-term adoption intentions (Duong, 2024).

The reinforcement cycle between convenience and social influence is that the more students observe other people getting value out of AI, the more they feel compelled to seek it out, and the more they experience the convenience, the more inclined they are to refer others to it (Li, 2023). Such interdependence leads to the quick growth of AI applications in the learning process as well as real life, creating a new behavioural standard where AI is not only a tool but is a part of the academic and life ecosystem of students.

2.4 Conceptual Framework

Figure 2.5

Conceptual Framework



Note. This figure was created by the author Chin Yin Tong.

2.5 Hypothesis Development

This section examines empirical studies, understands the relationships between variables, and formulates a hypothesis outlining the relationship between dependent and independent variables.

2.5.1 Digital Literacy

The first pair of hypotheses studies the association between the digital literacy of students and their learning performance when employing AI. This connection is explained by the fact that digital literacy is the basis for students to organize, analyse, and implement AI systems effectively. Students who are more digitally literate are usually more confident in their use of technological platforms, are more functional in troubleshooting, and are able to comprehend it more to prompt or engage AI tools to reap the most advantages (Yaseen et al. 2025). In case students do not have such skills, they might fail to use AI properly, and thus they might become frustrated, abuse it, or engage in superficial interaction that fails to add value to the learning process. Thus, the alternative hypothesis that the relationship between digital literacy and learning efficiency is positive is supported by the theoretical framework, providing the Technology Acceptance Model (TAM), which focuses on the user's capability in determining technology-based results. The null hypothesis, in its turn, presupposes that there is no such relation, and it, in turn, enables the research to find out whether digital literacy has any significant effect on students' enjoyment of AI, no matter their level of technological skills (Lo, 2024).

Revamping the digital literacy of students elevates their skills to handle learning tools and level of confidence to adapt to a modern learning environment. Intensifying digital literacy is remarkable for students to influence their attitudes towards adapting to learning processes linked with digital tools (Junaedi et al. 2023). Increasing the confidence of students to handle AI-based learning tools boosts their intention to embrace ChatGPT for refining their learning outcomes.

H1: There is a positive relationship between the digital literacy of students for using AI and their learning efficiency

2.5.2 Perceived Usefulness

The second hypothesis conjecture is concerned with the AI usefulness perception and its relationship with the learning efficiency. This interdependence is fairly grounded on TAM as it views the usefulness as a significant variable that dictates the success of the successful implementation of any form of technology in any learning environment. Those students who believe that AI tools can help them acquire a deeper understanding of concepts, save time, improve the quality of their academic output, or allow them to experience personalised learning, use it habitually and intentionally (Singh, 2024). The behavioural intention that follows is generally an improvement in academic performance and further learning performance because students are tactical in their use of AI to clear doubts, practise, summarise information, or generate insights. The second hypothesis based on the perceived usefulness and learning efficiency being directly related is premised on the fact that perceived usefulness of the tool directly affects its usefulness. Students will not make

much use of the AI, and its impact on the learning outcome will be insignificant in case students find it unhelpful or irrelevant.

Positive perception of students is functional in the matter of their willingness to enlist AI-driven tools, especially ChatGPT. With the aid of positive perception of students about implications of embedding AI in learning fortify their willingness to adopt this technology (Al-Mamary et al. 2024). Providing personalised learning along with accessible materials is remarkable aspects interrelated with AI-driven learning tools that affects students' attitudes to embrace technology.

H2: There is a close connection between the perceived usefulness of AI and students' learning efficiency.

2.3.3 Convenience and social influence

The third hypothesis pair examines the existence of a connection between convenience and social influence on the learning efficiency of using AI-based tools. This rationale is based on the theory, like the Unified Theory of Acceptance and Use of Technology (UTAUT), which states that effort expectancy (convenience) and social influence are crucial factors in the use of technology (Budhathoki et al. 2024). Social influence is also a significant factor since recommendations or the recommendation of peers, teachers, or family members have a higher chance of making students more confident in their attempts to try and implement AI tools. Positive social norms decrease the level of uncertainty and justify the usage of AI related to academic activities, and a student is more likely to use these tools successfully. Consequently, learning efficiency can be improved indirectly by both convenience and social influence that determine the behaviour and attitude toward technology adoption (George

& Wooden, 2023). The second hypothesis is that they actually relate to learning efficiency, whereas the null hypothesis is that the factors are not related, and the research can explore whether the social and practical context in which AI is used has a substantial impact on the learning performance of students.

Enlisting AI-driven learning tools by students is connected with their convenience and influence of others. A consequential factor in the matter of nurturing students' intent to embrace AI-driven learning method is the social influence (Zaman et al. 2025). By dint of advocacy of peers and convenience of using technologies, students might attenuate their fear about complexity of ChatGPT and uplift academic performance.

H3: There is a relationship between convenience and social influence regarding using AI-based tools and students' learning efficiency.

2.6 Literature Gap

This literature focused on the assimilation of different secondary information from past articles and journals. Incorporating secondary information from other articles could cause the issue of establishing the validity of previous data. This literature delineates the relationships of variables in this study, which includes the positive influence of AI on learning processes and outcomes for students. Encompassing AI-based technology, specifically ChatGPT, in the learning activities of students might cause several negative impacts. The prominence of integrity issues in the learning materials generated through ChatGPT is neglected in this literature. Avoiding the negative aspects interrelated with embracing AI-based learning tools creates gaps in this literature.

2.7 Conclusion

This section highlights the implications of embracing AI-driven learning technology, specifically ChatGPT, on the learning functions of students. Encompassing AI-based learning tools is vital for students to access personalised resources which drive their efficiency in learning activities. Consequences of digital literacy and perceived usefulness of students regarding the intention to embrace AI-driven tools and their impacts on their learning are evaluated. Implications of the convenience of using AI on the students' intention to adopt this technology for amplifying outcomes of their academic performance are mentioned. Integrating ChatGPT by students through social influence to affect their learning procedures is assessed in this literature. Congruous theories which affect the intention of students towards embracing AI in their learning processes are portrayed. Hypotheses of this study are formulated in this chapter to spotlight relationships among different variables.

CHAPTER 3: METHODOLOGY

3.0 Introduction

In this chapter, the research approach applied to accomplish the research objectives and verify the research hypotheses were covered. The research design helps to ensure the match of methods and research purpose, which the causal research helps us to figure out the relationship among variables. Quantitative research enables a clear communication while dealing with the collected data that are numerical. Sampling design is known as the method to collect data from a small portion from target population, and the samples collected allow us to obtain significant data for our research questions without accessing the entire target population. On the other hand, the data collection method refers to the process of finding relevant resources and gathering appropriate data to answer the research problems. The proposed data analysis tool is implemented to evaluate the reliability and validity of collected data from the samples. Finally, the conclusion is included as the last section in chapter 3.

3.1 Research Design

The design of the research is the plan of the researcher in relation to how they will assemble all the elements of the study; it provides an important guideline regarding how data will be collected, measured and analyzed.

3.1.1 Quantitative Research

Generally, in quantitative research, we can see figures and charts that are used to express the results obtained from the data collected. Quantitative research is used to validate theories and assumptions and establish generalized facts about a proposed topic. The commonly known quantitative research procedures include experiments, observations, and surveys, all of which are used to establish the relationship between two variables, then confirm the existing theory based on the findings. In short, quantitative research is implemented in this study, in which we will distribute surveys and collect data from university students.

3.1.2 Causal Research

Causal research is known as conclusive research in which researchers try to determine or figure out the relationship among the selected independent, moderating and dependent variables. Causal research is like descriptive research, in which both attempt to exhibit whether a proposed idea is practical. The difference between causal research and descriptive research is that the former seeks to identify the cause-and-effect factors, while the latter serves several goals for describing certain ideas, attitudes, and actions (Pratap, 2019). This study aims to determine the effect of independent variables on students' learning efficiency and test the moderating effect of intention to use AI , therefore causal research will be applied to this study.

3.2 Sampling Design

Following the formulation of the research design, a sampling design is developed. A proper sampling design is essential and necessary in establishing and boosting generalizations. As a result, the following subsections justify the current study's target population, sampling frame, sampling technique, and sample size.

3.2.1 Target Population

Since this study examines the impact of AI such as ChatGPT on students' learning efficiency, guided by the independent variables: digital literacy, perceived usefulness, convenience and social influence, and the moderating variable: intention to use AI, thus the target population will be a group of university students enrolled in higher education institutions in Malaysia. University students are selected because they are among the most active users of AI-based tools such as ChatGPT in academic learning and personal routines.

3.2.2 Sampling Frame

A sampling frame is the exact pool of respondents from which the sample is drawn (MacKinnon, 2021). There is no sampling frame used in this study, as this study uses non-probability sampling techniques.

3.2.3 Sampling Technique

The sampling technique refers to the strategy for choosing certain individuals or a subset from a population, then drawing conclusions statistically and estimating the characteristics of the entire population (Fleetwood and Rahman et al., 2022). Non-probability sampling is used in this study because it is difficult to access the entire population, making it impossible to give everyone an equal chance of selection. Convenience sampling is applied due to the absence of a formal sampling frame. This method is chosen to efficiently gather many responses within a short time.

3.2.4 Sampling Size

A survey questionnaire will be sent to 500 university students as an online form through Microsoft Teams, WhatsApp and/or other social media outlets to ensure that there will be a substantial number of respondents.

3.3 Data Collection Method

Data is a collection of facts and information gathered from different origins, and data collection method refers to the methodological process of gathering data. The subsection below describes the type of data that used on searching and collecting relevant information for this study.

3.3.1 Primary Data

In this study, all data will be primary data since they are obtained from respondents through a questionnaire. All primary data will be gathered from the respondents by using a Google Form survey, and the survey will be distributed to each respondent via various messaging platforms like e-mail, wechat and telegram. In addition, the survey will be posted on social media such as Facebook and Instagram to reach a wide number of target populations effectively.

3.4 Proposed Data Analysis Tool

Structural equation modeling, also known as SEM, refers to a group of statistical techniques for measuring the correlations between observed and latent variables (Beran & Violato, 2010). There are two types of SEM which the Covariance-based SEM (CB-SEM) applies factor model to represent latent variables, while the Partial Squares SEM (PLS-SEM) models the latent variables using composites (Cepeda- Carrion et al., 2019).

3.4.1 Partial Least Squares Structural Equation Modeling

In this study, the data collected will be analyzed by the Partial Least Squares Structural Equation Modeling (PLS-SEM) in the Smart PLS 4 software to perform the model assessment. Cepeda-Carrion et al. (2019) stated that PLS-SEM is a latent variable model based on variance. Haji-Othman et al.,(2024) explained that the PLS-SEM provides secured and coherent method with data

requirements, model complexity, and relationship specification for data analyzing. There are two main steps. First, check the measurement model to see if it is reliable and valid. If it looks good, then move on to the next step, the structural model as explained in Partial Least Square Structural Equation Modelling (PLS-SEM) in Knowledge Management Studies: Knowledge Sharing in Virtual Communities, (2022). The second stage determines the significance and meaningfulness of the structural relationship between models, and the hypotheses are also being evaluated in this stage.

3.5 Research Instruments and Construct Measurement

As mentioned in previous section of 3.3.1, this study uses survey questionnaires to collect data from respondents which this method could provide the ease in result computing process. The questionnaire was distributed to reach more respondents, using English as it is the global official language. Simple language was used to prevent confusion and ensure the accuracy of the results.

The questionnaire uses structured multiple-choice questions for convenience and efficiency for respondents to answer. The questionnaire is divided into two sections. Section A covers the demographic profiles questions, covering respondents' gender, age, university studied, programme, year of study and frequency of using ChatGPT.

Section B, the questions are grouped in five subsections to construct measurement that were included for all variables. A Likert scale with five-point is applied to estimate the degree of agreement and disagreement with various statements, and to measure perceptions of impact on learning, skills, and daily life. Table 3.1 below shows all the

details of Section A. All questions were developed to lead us to identify the right target respondents that the details of each demographic questions

Table 3.1

Research Instruments and Measurement Scale of Section A

Question	Options	Construct Measurement
Gender	Male Female	Nominal
Age	17-20 years old 21-24years old 25-28 years old Above 28 years old	Ratio
University studied	Universiti Tunku Abdul Rahman(UTAR) Tunku Abdul Rahman University of Management and Technology (TARUMT) UCSI University Sunway University Others: Monash University Malaysia, Asia Pacific University of Technology & Innovation (APU),Taylor’s University,etc	Interval
Programme	Arts and Design(Graphic Design, Fashion Design) Business (Business Administration, Accounting and Finance,Marketing) Information Technology(IT)	Interval

Engineering(Software Engineering, Mechanical Engineering)
 Others: Health Sciences and Medicine, Law, Hospitality and Tourism, etc.

Year of Study	Year 1 Year 2 Year 3 Final Year	Interval
Frequency of using ChatGPT	Never Rarely(1-2times) Sometimes(3-5times) Often(6-10times) Very often(more than 10times)	Ratio

Note. This table summarizes the demographic and ChatGPT usage questions from Section A of the research questionnaire. The questions were developed by the researcher for this study.

Table 3.2

Section B

Source(s)	Construct	Item	Questions	Construct Measurement
Aydınlar et al. (2024)	Digital Literacy	DL1	I am aware that artificial intelligence is included in the technologies we use in our daily lives.	Interval

Yaseen et al. (2025)		DL2	Through digital literacy, I have learn better with the use of interactive AI tools.	
Baskara (2024)		DL3	I know how I can use AI in academic work ethically and responsibly.	
		DL4	I am able to discover core competencies such as data-handling capabilities for future careers.	
Muhammad (2025)		DL5	I believe that AI use improves my ability to solve problems.	
Schei et al. (2024)	Perceived Usefulness	PU1	My self-efficacy and motivation for task resolution is enhanced with the use of AI tools.	Interval
		PU2	It is through AI that I am able to work on tasks or assignments more effectively.	
		PU3	The use of AI applications makes learning more interactive and efficient.	

		PU4	I consider AI tools useful for understanding difficult topics or concepts.	
Linus et al. (2025)		PU5	In general, AI technologies can be considered useful to my academic activities.	
Linus et al. (2025)	Convenience and Social Influence	CASI1	The idea of learning how to utilize AI tools to improve learning results is easy to me.	Interval
		CASI2	In general, AI technologies can be considered useful to my academic activities.	
Aldraiweesh and Alturki (2025)		CASI3	I find AI tools straightforward to operate for my learning activities.	
		CASI4	My friends or classmates encourage me to use AI for learning tasks.	
		CASI5	Using AI makes me feel more accepted or connected with others who use similar technologies.	

Lien et al. (2025)	Intention to Use AI	ITUA1	I believe the application of AI in education is an excellent and productive activity.	Interval
		ITUA2	I am comfortable relying on quality of AI tools when performing academic tasks.	
Seo et al. (2021)		ITUA3	I think learning with the help of AI tools is more enjoyable and interesting.	
Saklaki and Gardikiotis (2024)		ITUA4	The attitude toward my studies with the help of AI tools is positive.	
		ITUA5	I will keep utilizing AI tools to aid my learning and personal activities.	
Kamalov et al. (2023)	Students' Learning Efficiency	SLE1	My learning activities have become more efficient with the help of AI tools.	Interval
		SLE2	The use of AI has helped me to manage my time and daily routine positively.	

- SLE3 I also believe that I am more competent to do tasks with the assistance of AI.
- SLE4 AI has helped me advance the quality of my education by providing out-of-box responses.
- SLE5 My way of approaching problem solving in my everyday life has considerably been modified by the use of AI.
-

Note. This table presents the measurement items for the key constructs in Section B of the research questionnaire. The items were adapted from validated scales in existing academic literature, with the original sources cited in the first column. All items were measured using a 5-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree).

3.6 Data Analytics Techniques

The survey will be pilot tested prior to distribution, which serves to identify and correct any possible deficiencies in the survey and/or provide additional benefits such as

verification of the simplicity and clarity of the questions provided to students for response. Once all potential issues were resolved, the pilot survey was issued. In the following subsections, they primarily cover the brief explanation of the pilot test study, the descriptive analysis, and the inferential analysis conducted in this study.

3.6.1 Pilot Test

The respondents have been given the questionnaire, and they were voluntarily involved and confidentiality and anonymity were taken into account for enhancing overall questionnaire results. Besides, the Cronbach Alpha was applied in this study to determine the reliability of the measurement items. In order to discover whether there is any measurement item with low reliability, the threshold >0.6 was applied that the values lower than 0.6 will be considered as low reliability.

3.6.2 Descriptive Analysis

The descriptive analysis was carried out to describe and demonstrate the respondents' demographic data such as age, gender, university studied, programme, year of study and frequency of using ChatGPT. All of these details were summarized and displayed in the form of table, along with the percentage of respondents. Besides, the descriptive data were being adapted from Google Form and were analysed by using Microsoft Excel.

3.6.3 Inferential Analysis

To conduct an inferential analysis, the Structural Equation Modeling (SEM) was chosen. It is a set of statistical techniques that measures and analyses the relationships between the observed and latent variables. Besides, SEM examines the linear relationships among variables while also simultaneously determining potential measurement errors (Beran & Violato, 2010).

The Partial Least Squares Structural Equation Modeling (PLS-SEM) is chosen for this study instead of the Covariance-based SEM (CB-SEM). In selecting this method of research, the primary reason is the prediction of future events. The research method of PLS-SEM allows researchers to achieve their maximum explained variance (R^2) results which matches the study's purpose of finding essential factors that determine Students' Learning Efficiency. CB-SEM requires a larger amount of sample size in a full information approach, while PLS-SEM separates the model into smaller components for each construct (Astrachan et al., 2014 ; Hair & Alamer, 2022 ; What Is the Difference between PLS-SEM and CB-SEM and at What Stage Do You Use the Two? | ResearchGate, 2023). PLS-SEM consists of two-stage procedures, which namely the measurement model, and the structural model. The entire PLS-SEM analysis was done by using the SmartPLS 4.0 version.

As supported by Cheung et al.(2023), in the measurement model assessment, the internal consistency reliability, indicator reliability, convergent validity, as well as the discriminant validity were examined. First of all, the internal consistency reliability is measured by the composite reliability which take consideration of different outer loadings of all measurement items. The indicator reliability is measured by the outer loadings, while the convergent validity is measured by the Average Variance Extracted (AVE). Lastly, the discriminant validity is measured by the HTMT ratios (Malik et al., 2021).

Table 3.3

Rules of Thumb for Reflective Measurement Model

Assessment	Criteria	Threshold
Internal consistency reliability	Cronbach's alpha Composite reliability Reliability coefficient	$>0.6 \leq 0.9$
Reflective indicator reliability	Indicator loadings	≥ 0.708 , eliminate the indicators with low loadings (<0.4).
Convergent validity	AVE	≥ 0.5
Discriminant validity	HTMT	< 0.9

Note. This table outlines the assessment criteria and recommended thresholds for evaluating the reliability and validity of the reflective measurement model by Hair et al, 2021, Partial Least Squares Structural Equation Modeling (PLS-SEM) Using R. Cham: Springer.

On the other hand, there are three assessments tested in the structural model, including the collinearity assessment, the significance of relationship, and the model explanatory power. The collinearity assessment is tested by Variance Inflated Factors (VIF) to determine any potential collinearity issues, while the significance of relationship is measured by the t-value for identifying the relationship among the exogenous and endogenous variables (Kim, 2019). Last but not least, the model explanatory power is measured by the Coefficient of

determination, known as R², to find the percentage of variance from endogenous variable explained by the exogenous variable (Pakay, 2023) .

Table 3.4

Rules of Thumb for Structural Model Assessment

Assessment	Criteria	Threshold
Collinearity	Variance Inflated Factors(VIF)	<3.0
Significance of Structural Model Relationships	Significance of Path Coefficients	t-values is significant at 0.05
Model Explanatory Power	Coefficient of Determination (R ²)	0.75 – substantial 0.5 – moderate 0.25 – weak

Note. This table presents the assessment criteria used to evaluate the structural model and test the hypothesized relationships between the research constructs.

3.7 Conclusion

To summarize, this chapter outlines the research design including the causal research and quantitative research, the sampling design which covers the target population, sampling frame and sampling technique. Moreover, the data used in this study are

collected through primary data, and the partial least squares structural equation modeling (PLS-SEM) is used for data analysis and model assessment. In the next chapter, it will cover about the analysis of data collected, which are the descriptive analysis and the inferential analysis.

CHAPTER 4: DATA ANALYSIS

4.0 Introduction

The chapter presents the data analysis and results of the study on the influence of AI tools, especially ChatGPT, on the learning efficiency and everyday lives of university students. The main constructs in the study are Digital Literacy (DL), Perceived Usefulness (PU), Convenience and Social Influence (CASI), Intention to Use AI (ITUA), and Students' Learning Efficiency (SLE), which constitute the Main Model AI ChatGPT. This chapter, in line with the thesis's purposes, outlines the initial data screening processes undertaken to ensure the dataset is complete and analysis can proceed. It will then provide a descriptive analysis of the respondents' demographic characteristics and the general trends in the key constructs. This is followed by evaluating the measurement model against the criteria of indicator reliability, internal consistency reliability, convergent validity, and discriminant validity. Lastly, the structural model is used to test the proposed hypotheses using Partial Least Squares Structural Equation Modelling (PLS-SEM) in SmartPLS 4.0, with bootstrapping for significance testing, to answer the study's objectives. The selection of PLS-SEM is particularly appropriate for this study because it enables the analysis of complex models which contain multiple constructs and it provides robust support for both exploratory research and confirmatory research. PLS-SEM uses different methods to predict dependent variables because it requires researchers to identify all necessary predictors which makes it suitable for social science studies that involve non-normal data patterns. The approach concentrates on increasing explained variance of Students' Learning Efficiency as the primary endogenous construct in the analysis.

4.1 Preliminary Data Analysis

4.1.1 Data Screening and Missing Values

Data used in this research were obtained using an online self-administered questionnaire that was taken by university students studying different programmes. Overall, the responses were downloaded (511) into Excel and are ready to be imported into SmartPLS 4.0. The first screening included the deletion of non-analytic columns (e.g., the metadata generated by the system), verification of whether all items were coded using the target 15 Likert scale, and verification that a complete set of responses was present regarding the key constructs Digital Literacy, Perceived Usefulness, Convenience and Social Influence, Intention to Use AI and Students' Learning Efficiency (Bashar Haruna Gulumbe et al., 2024). Multi-submissions were not found, and no instances of extensive data gaps were found. Similarly, there were no evident straight-line response patterns on scanning the item distributions and response frequencies. Consequently, the number of cases that were retained to be further analysed was 511, which is a strong sample size for PLS-SEM.

4.1.2 Common Method Bias

In SmartPLS 4.0, the common method bias was evaluated with the help of collinearity statistics. The VIF values on the inside were between 1.000 and

3.541. Even though one predictor was slightly above the more rigid 3.3 guideline, the VIF values were all below the standard value of 5. This implies that no serious common method bias and multicollinearity issues were expected to jeopardize the structural estimates.

4.1.3 Reliability Pilot Test

Before the actual data collection, a pilot study was carried out in order to determine the clarity and reliability of the instrument (Kambhampati & Patel, 2025). All the construct alpha values were greater than 0.60 in the pilot, which means that there is acceptable internal consistency and justifies the conclusion that the refined questionnaire would be used in the full-scale survey with 511 respondents.

4.2 Descriptive Analysis

4.2.1 Respondents' Demographic Profile

The ultimate sample of this study included 511 students of the university. According to Table 4.1, most of the respondents were female ($n = 320$, 62.6%), and 191 cases were male students (37.4%). The majority of the respondents were aged between 21 and 24 years ($n = 337$, 65.9%), and secondly, there were those aged 17 years to 20 years ($n = 110$, 21.5%). Lower percentages were in

the 2528 years age group (n = 46, 9.0) and that of more than 28 years (n = 18, 3.5), which means that the sample is mostly representative of the average university-age students (Bashar Haruna Gulumbe et al., 2024). As far as the institutional affiliation is concerned, the highest number of respondents were students of Universiti Tunku Abdul Rahman (UTAR) (n = 334, 65.4%), followed by those of Tunku Abdul Rahman University of Management and Technology (TAR UMT) (n = 54, 10.6%). The UCSI University (n = 30, 5.9%), the Sunway University (n = 18, 3.5%), and the ones outside UCSI University like the Monash University Malaysia and Asia Pacific University of Technology and Innovation (APU) had a smaller number, but the college population was 75 (14.7%). Programme-wise, over half of the sample were pursuing Business-related programmes (n = 277, 54.2%), the rest were pursuing Information Technology (9.2%), Engineering (9.6%), Arts and Design (7.2%), and other fields such as Health Sciences, Medicine, Law, and Hospitality (19.8%).

Table 4.1

Respondents' Basic Demographic Profile

Demographic Variable	Category	Frequency (n)	Percentage (%)
Gender	Female	320	62.6
	Male	191	37.4
Age	17–20 years old	110	21.5
	21–24 years old	337	65.9
	25–28 years old	46	9.0
	Above 28 years old	18	3.5
Education Institutions	Universiti Tunku Abdul Rahman (UTAR)	334	65.4
	Tunku Abdul Rahman University of Management and Technology (TAR UMT)	54	10.6
	UCSI University	30	3.5
	Sunway University	18	5.9
	Others: Monash University Malaysia and Asia Pacific	75	14.7

University of Technology and Innovation (APU), Taylor's University, etc

Programme	Arts and Design(Graphic Design,Fashion Design.etc)	37	7.2	
	Business(Business Administration,Accounting,and Finance,Marketing,etc)	277	54.2	
	Information Technology(IT)	47	9.2	
	Engineering(Software Engineering,Mechanical Engineering,etc)	49	9.6	
	Others:Health Sciences and Medicine,Law,Hospitality and Tourism,etc	101	19.8	
	Year of Study	Year 1	112	22.0
		Year 2	139	27.3
	Year 3	68	13.3	
	Final Year	192	37.7	
Frequency of ChatGPT use	Very often (more than 10 times)	227	44.4	
	Often (6–10 times)	159	31.1	
	Sometimes (3–5 times)	98	19.2	
	Rarely (1–2 times)	19	3.7	
	Never	8	1.6	

Note. The table displays the contents of Section A in the research questionnaire which aims to gather demographic information while assessing how often people use ChatGPT. The researcher created these items to develop a student sample profile which shows how students used the AI tool.

On the academic level, those who were in their final year of study (37.7%), Year 2 (27.2%), Year 1 (21.9%), and Year 3 (13.3%), constituted 192 (37.7), 139 (27.2), 112 (21.9), and 68 (13.3) respondents respectively. Such a distribution implies that the dataset represents the views of students at various stages of their educational progress, with a minor focus on older student groups (Almulla,

2022). The frequency of ChatGPT usage was high: 227 students (44.4%) said that they used it very often (more than ten times), 159 (31.1) often (six to ten times), and 98 (19.2) sometimes (three to five times). A scanty group of 3.7 and 1.6 percent seldom and never used ChatGPT, respectively. These statistics suggest that the AI tools and especially ChatGPT are already a part of the daily academic experiences of the vast majority of the respondents.

4.2.2 Descriptive Statistics of Main Constructs

The five latent constructs, which had been measured on a five-point Likert scale, also had descriptive statistics calculated. Mean composite scores were developed through averages of the items pertaining to each construct. Digital Literacy (DL) has the largest mean ($M = 4.20$, $SD = 0.71$) and Perceived Usefulness (PU) ($M = 4.16$, $SD = 0.76$) followed. The means of Convenience and Social Influence (CASI) and Intention to Use AI (ITUA) were also similar ($M = 4.08$, $SD = 0.70$ and $M = 4.07$, $SD = 0.74$, respectively). The mean of Learning Efficiency (SLE) among students was slightly lower but still positive ($M = 4.04$, $SD = .80$). The lowest possible score was 1 and the largest possible score was 5 in all constructs. All told, the average scores exceeding the scale mid-point of 3 suggest that the respondents were mostly interested in affirmative words and expressions regarding their digital literacy, attitude towards AI usefulness, social support and convenience regarding AI, intent to use AI and perceived increase in learning efficiency (Liu et al., 2025). The means of DL and PU are relatively higher, which indicates that students not only belong to the group who believe they are competent in using AI technologies but are also persuaded that it can be useful in assisting academic activities.

Table 4.2

Descriptive Statistics for Latent Constructs (Likert 1–5)

Construct	N	Mean	Standard Deviation	Minimum	Maximum
DL – Digital Literacy	511	4.20	0.71	1.00	5.00
PU – Perceived Usefulness	511	4.16	0.76	1.00	5.00
CASI – Convenience & Social Influence	511	4.08	0.70	1.00	5.00
ITUA – Intention to Use AI	511	4.07	0.74	1.00	5.00
SLE – Students’ Learning Efficiency	511	4.04	0.80	1.00	5.00

Note. This table presents the descriptive statistics for the main research constructs based on the final sample of N = 511 respondents. The study used a 5-point Likert scale for all constructs which defined 1 as "Strongly Disagree" and 5 as "Strongly Agree." The participants showed positive views about AI usage through their high mean scores which they used to assess their intentions to use the technology.

4.3 Measurement Model Assessment (Reflective Constructs)

The measurement model was evaluated, and then the structure of the relationship was tested. The conceptualization and modelling of all five latent constructs of this research, Digital Literacy (DL), Perceived Usefulness (PU), Convenience and Social Influence (CASI), Intention to Use AI (ITUA) and Students Learning Efficiency (SLE) were in the form of reflective variables. In this line, the measurement model was tested in accordance with standard procedures of PLS-SEM, which entails measurement of indicator reliability, internal consistency reliability, convergent and discriminant validity (Mahmud, 2024). The findings of the analysis based on SmartPLS 4.0 reveal that the Main Model AI ChatGPT has acceptable psychometric characteristics and may be relied on to assess the structural connections between the constructs, but the support of the discriminant validity is higher by the Fornell-Larcker convention compared to the more rigorous HTMT requirement.

4.3.1 Indicator Reliability (Outer Loadings)

The reliability of indicators was determined by looking at the outer loadings of the indicators on the respective reflective constructs of the SmartPLS measurement model. The importance of outer loading analysis is that it demonstrates the strength of each of the observed items to reflect the latent variable that the item is expected to measure. Outer loading of 0.70 and above is generally deemed acceptable; however, in PLS-SEM, it implies that the construct accounts for a significant percentage of the variance in the indicator (Lund et al., 2025). All items in this research got loadings that were higher than

the recommended minimum, and so this proves that the indicators were the right measures of what they were designed to measure. All five measures were substantially linked with digital literacy (DL) (0.827, 0.874, 0.869, 0.795, and 0.804). With loadings of 0.846, 0.885, 0.863, 0.865, and 0.884, the PU indicators performed well.

The Convenience and Social Influence (CASE) case had comfortable item loadings of 0.824, 0.838, 0.828, 0.780, and 0.777. The Intention to Use AI (ITUA) construct has indicator reliability loadings of 0.855, 0.827, 0.833, 0.899, and 0.849. High indicator loadings for Students Learning Efficiency (SLE) were 0.848, 0.866, 0.891, 0.873, and 0.845. The found item dependability in each of the five categories ranges between 0.777 and 0.899, which implies high reliability. No indications that were below 0.70 were eliminated since there were no such indications. The reliability of indications was high in the next study, so all measurement items were retained.

Table 4.3

Outer Loadings for Reflective Indicators

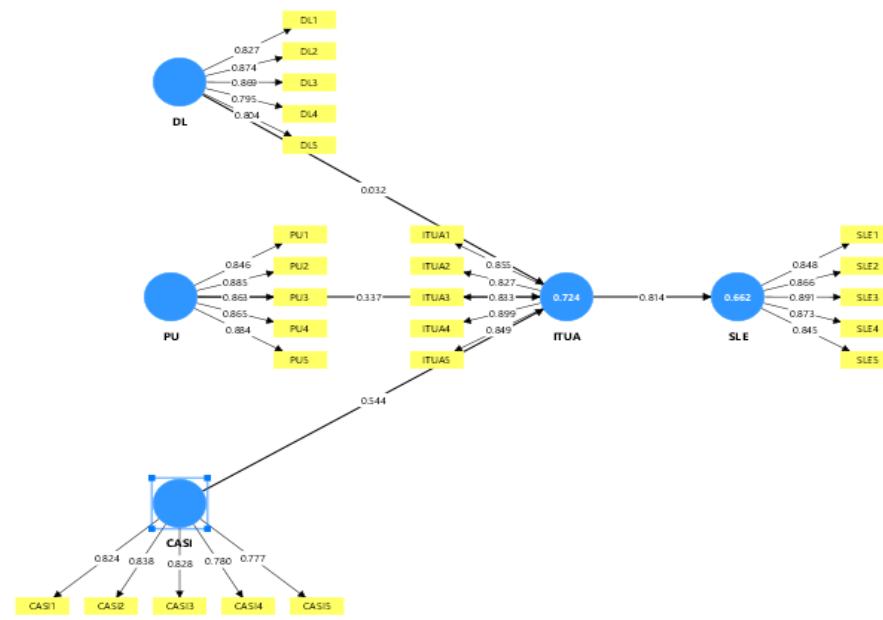
Construct	Item code	Outer loading	Decision
Digital Literacy (DL)	DL1	0.827	Retained
	DL2	0.874	Retained
	DL3	0.869	Retained
	DL4	0.795	Retained
	DL5	0.804	Retained
Perceived Usefulness (PU)	PU1	0.846	Retained
	PU2	0.885	Retained
	PU3	0.863	Retained
	PU4	0.865	Retained
	PU5	0.884	Retained
Convenience & Social Influence (CASI)	CASI1	0.824	Retained
	CASI2	0.838	Retained
	CASI3	0.828	Retained

		CASI4	0.780	Retained
		CASI5	0.777	Retained
Intention to Use AI (ITUA)		ITUA1	0.855	Retained
		ITUA2	0.827	Retained
		ITUA3	0.833	Retained
		ITUA4	0.899	Retained
		ITUA5	0.849	Retained
Students' Learning Efficiency (SLE)		SLE1	0.848	Retained
		SLE2	0.866	Retained
		SLE3	0.891	Retained
		SLE4	0.873	Retained
		SLE5	0.845	Retained

Note. This table shows the outer loadings for the reflective indicators. The decision to retain an item was based on the recommended threshold of an outer loading of 0.708 or higher. All items met this criterion.

Figure 4.1

SmartPLS 4.0 analysis



Note. This figure presents the final structural model illustrating the results of the hypothesis testing. The values on the arrows represent the path coefficients (β) and the corresponding t-values in parentheses. The results show that all hypothesized paths (H1, H2, H3, H4) are statistically significant and supported.

4.3.2 Internal Consistency Reliability (Cronbach's Alpha and Composite Reliability)

The indicators within each construct were tested for internal consistency reliability to ensure they measured the same notion consistently. This assessment is the main point before any structural correlations are interpreted in PLS-SEM, to find out whether the model is grounded in good measure. Cronbach's alpha, rho A and composite reliability (RC) were used to find out internal consistency reliability. Since Cronbach's alpha is a conservative value, rho A is a better approximation of the reliability of PLS models, and composite reliability must be used to indicate the actual outer loadings; the statistics give a more balanced perspective of reliability than when using a single measure (Rojas Contreras et al., 2025).

This demonstrates that Digital Literacy, Perceived Usefulness, Convenience and Social Influence, Intention to Use AI, and Students' Learning Efficiency were similar to reliable reflective scales. It is not true to say that reliability demonstrates conceptual power. High reliability indicates that objects move in concert, a lot, but does not indicate that the construct is theoretically one-to-one or meaningful (Rojas Contreras et al., 2025). The good internal consistency of this study indicates that the scales do not appear to be fragmented or unstable,

but it needs to be considered with convergent and discriminant validity to avoid simplification. In this way, the results of the reliability test help to make a judgment regarding the model and ensure that the constructs are statistically reliable to make an interpretation of the structural model.

Table 4.4

Internal Consistency Reliability and Validity

Construct	Cronbach's Alpha	Composite Reliability (ρ_c)	rho_A	Decision
DL	0.891	0.919	0.891	Retained
PU	0.919	0.939	0.919	Retained
CASI	0.869	0.905	0.872	Retained
ITUA	0.906	0.930	0.907	Retained
SLE	0.915	0.937	0.916	Retained

Note. This table presents the assessment of internal consistency reliability and validity for all research constructs. Cronbach's Alpha, Composite Reliability (ρ_c), AVE and rho A are used to measure the consistency of the indicators within each construct.

4.3.3 Convergent Validity (Average Variance Extracted – AVE)

To assess convergent validity, the measurement error was assessed using the Average Variance Extracted (AVE) which is the average amount of variance a construct captures among its indicators. Since it measures the convergent of observable variables on the same latent concept as opposed to the chance of two variables correlating, such a criterion is essential in reflective measurement. The AVE of all constructs in this research was above 0.50, and this implies that

they accounted for more than half the variance in their indicators. This statistically indicates that the meanings of the indicators of each construct are the same (Salem Belhaj, 2025). The result is in line with the argument that the constructs are internally consistent and substantively unified analytically.

As a matter of practise, it implies that the questions, which are supposed to assess the usefulness, social and contextual convenience, intention, and learning efficiency, capture bigger dimensions of the student engagement with AI technologies. The convergent validity is to be questioned (Salem Belhaj, 2025). Above threshold AVE values represent that there is convergence, but not that constructs are non-overlapping. In cases where the concepts involved are very similar, a model can have good convergence but low discriminant validity.

Table 4.5

Convergent Validity (Average Variance Extracted – AVE)

Construct	AVE	Threshold (≥0.50)	Decision
DL	0.696	Achieved	Convergent validity met
PU	0.755	Achieved	Convergent validity met
CASI	0.656	Achieved	Convergent validity met
ITUA	0.728	Achieved	Convergent validity met
SLE	0.748	Achieved	Convergent validity met

Note. This table presents the assessment of convergent validity using the Average Variance Extracted (AVE). The AVE for a construct represents the extent to which the variance attributable to a particular indicator (for measuring an attribute) is greater than the measurement error variance associated with that indicator. A construct's AVE should be at least 0.50, indicating that the construct's measurement errors account for less than 50% of the total variance; therefore, since all the constructs in this study had AVE values that exceeded 0.50, convergent validity has been established in the measurement model.

4.3.4 Discriminant Validity

The discriminant validity of the heterotrait monotrait ratio (HTMT) and the Fornell-Larcker criterion was studied. This step is important as a model may appear to be reliable and convergent, but may overlap its concepts with other constructs. The square root of the AVE of each construct exceeded its correlations with the other constructs, which met Fornell-Larcker criteria. This implies that each of the latent variables has more indicator variance than variance with rival constructs (Hair et al., 2021). It is only then that the model is acceptable. Nevertheless, there should be more scrutiny of the HTMT results. The HMTMT values were between 0.804 and 0.917, with some values being below 0.95, but very few above 0.90. It demonstrates the empirical similarity of CASI with similar constructs, especially those that are associated with learning outcomes and behavioral intention.

The fact that the model is so close does not make it invalid, but it creates an interpretation problem: CASI might be a facilitator of context and a motivating influence, and thus its boundaries are less visible than those of a more limited construct. This is prevalent in behavioural research where the combination of social approbation, convenience, and environmental facilitation is involved. It implies that discriminant validity in this study is not ideal, but rather satisfactory (Salem Belhaj, 2025). The model satisfies the simple continuation conditions, but the HTMT trend indicates that the conceptual enhancement of CASI can enhance the future structures. Although the construct is not as unique as it would be preferred, the evidence is in favor of keeping it.

Table 4.6

HTMT Ratios Between Constructs

	DL	PU	CASI	ITUA	SLE
DL	–	0.860	0.901	0.808	0.852
PU	0.860	–	0.813	0.832	0.804
CASI	0.901	0.813	–	0.917	0.914
ITUA	0.808	0.832	0.917	–	0.892
SLE	0.852	0.804	0.914	0.892	–

Note. This table presents the Heterotrait-Monotrait (HTMT) ratios to assess discriminant validity. The HTMT ratio between constructs in a model must be less than 0.90. The majority of construct pairs had HTMT ratios that met this threshold, but HTMT ratios between CASI and DL (0.901); CASI and ITUA (0.917); CASI and SLE (0.914) all exceeded this threshold. This suggests construct CASI has likely not achieved discriminant validity, which means the 'Convenience & Social Influence' construct is likely not sufficiently unique from Digital Literacy, Intention to Use AI, and Student's Learning Efficiency constructs in this study.

Table 4.7

Fornell–Larcker Criterion

	DL	PU	CASI	ITUA	SLE
DL	0.835				
PU	0.778	0.869			
CASI	0.784	0.718	0.810		
ITUA	0.725	0.757	0.811	0.853	
SLE	0.768	0.734	0.811	0.810	0.865

Note. This table assesses discriminant validity using the Fornell–Larcker criterion. Each construct's square root of AVE (shown in bold on diagonal) must be greater than its correlations with all other constructs (shown in off-diagonal). This typically is true for most constructs; however, this was not true for CASI construct as its AVE was 0.810 which was lower than its correlation with ITUA (0.811) and SLE (0.811). Additionally, this provides evidence that CASI likely has not achieved discriminant validity with ITUA and SLE constructs; therefore corroborating the findings from the HTMT analysis provided earlier.

4.4 Structural Model Assessment

A structural model was evaluated to test the conceptual framework, which had been redesigned after deciding the suitability of the measurement model. The structural model was assessed to test the redesigned conceptual framework once the measurement model's suitability was established. DL, PU, and CASI were predictors of Intention to Use AI (ITUA) and Students' Learning Efficiency (SLE) in the final model (Zafar et al., 2024). In such a way, the framework does not presuppose that digital competency or positive attitudes are bound to increase efficiency, but it is important when it comes to the identification of meaningful AI usage. The significance of direct and indirect effects was estimated by bootstrapping using 5,000 resamples to enable the model to test the connections and intention as an intermediate channel. This separates the association between surfaces and the transmission of behavior, rendering it analytically applicable. The conceptual relevance of a predictor can be ineffective because it does not change the intention of the students. Such logic takes centre stage in the interpretation of the following facts.

4.4.1 Collinearity assessment

To ensure the predictors did not have too strong a correlation to corrupt the regression estimates, collinearity was considered using inner VIF values, and route correlations were assessed. The VIF values were 3.007 for CASI → ITUA, 3.541 for DL, 2.780 for PU, and 1.000 for ITUA → SLE. Values of all were less than the historical maximum value of 5, which means that there was no extreme multicollinearity. Upon further inspection, the VIF of DL was slightly above the 3.3 level. This does not weaken the model, but implies that the Digital Literacy is somewhat different from the variance of other intention antecedents. This is understandable, as AI can be useful and helpful to technologically literate students as well. The problem is interpretive, not statistical (Zafar et al., 2024). The result implies that DL is not an ideal predictor and can be rivaled by other variables to predict ITUA. It is of interest as to why DL is non-significant in the route model.

Table 4.8

Inner VIF Values

Hypothesis	Path	VIF
H1	DL → ITUA	3.541
H2	PU → ITUA	2.780
H3	CASI → ITUA	3.007
H4	ITUA → SLE	1.000

Note. The VIF measurement shows that critical collinearity problems exist when the value reaches 5 or above. The table demonstrates that all inner VIF measurements stay below 5 which shows values between 1.000 and 3.541. The VIF value of 3.541 for H1 Hypothesis exceeds the conservative threshold of 3 but stays within the acceptable limits which proves that multicollinearity does not pose major issues for the structural model.

4.4.2 Coefficient of determination (R^2) and effect sizes (f^2)

The coefficient of determination was used to test the model in explaining the phenomenon. The intention to use AI was explained by DL, PU, and CASI with an R^2 of 0.724 and a variance of 72.4%. Student Learning Efficiency R^2 was 0.662, meaning that ITUA accounts 66.2% of the Learning Efficiency variance. The fact that these values are this high indicates the redesigned framework is very explanatory. Notably, this implies that the model is significant and applicable in practice (Kang & Ahn, 2021). The readiness to utilize AI explains a good deal of the measured learning effectiveness of students, suggesting that AI has a centralized impact on academic performance. The fact that the R^2 of ITUA is high suggests that the attitudinal and contextual factors in the model affect the intention of students not equally.

The effect size analysis determines the extent to which each of the external constructs predicts the endogenous variable variance. CASI had a considerable impact on ITUA ($f^2 = 0.357$), PU had a near-medium effect ($f^2 = 0.148$), DL had no effect ($f^2 = 0.001$), and ITUA considerably affected SLE ($f^2 =$ Values aid structural interpretation. CASI matters; it is the best predictor of intention, suggesting that comfort, ease of integration, and social approval are the forces

behind AI use rather than digital expertise. PU is important but of moderate impact, and its usefulness is persuasive but not overwhelming on its own.

4.4.3 Path coefficients and hypothesis testing

There was moderate bootstrapping support of the direct hypotheses. Students' AI goals were not significantly related to their digital literacy (0.032, $t = 0.457$, $p = 0.648$). ITUA was substantially affected by PU ($\beta = 0.337$, $t = 4.177$, $p < 0.001$), whereas CASI had a greater influence ($\beta = 0.544$, $t = 9.397$, $p < 0.001$). Specifically, ITUA substantially affected SLE ($\beta = 0.814$, $t = 27.158$, $p < 0.001$). The results indicate that behavioural intention is the most important relationship between perception and learning outcome (Kang & Ahn, 2021). The efficiency of students increases in cases when they see AI as useful, socially and practically motivated, and they want to use it. It is not disappointing but logically informative that the non-significance of DL. This means that capacity alone and without context and drive is insufficient.

4.4.4 Mediation Analysis

The trend was supported by a study of mediation. The indirect impact of DL on SLE via ITUA was insignificant ($\beta = 0.026$, $t = 0.455$, $p = 0.649$). ITUA substantially mediated the association between PU and SLE ($\beta = 0.275$, $t = 4.078$, $p < 0.001$) and CASI and SLE ($\beta = 0.443$, $t = 9.018$, $p < 0.001$). This intention refers to usefulness and convenience/social impact being converted to learning efficiency (Sarstedt et al., 2019). Learning outcomes among students

are improved due to such views, causing them to be willing to put AI into practical application in their academic tasks, rather than being abstract. The indirect impacts of CASI are large, with a likely central focus on adoption and benefit on the supportive environment and ease of use.

4.4.4 Structural Model Results

The structural model analysis strongly supports the proposed research framework. The structural correlations were analyzed using SmartPLS 4.0 with bootstrapping, and no collinearity was observed. The model is explanatory with a big percentage of the Learning Efficiency difference among Students being explained by the predictors (Kang & Ahn, 2021). The combination of Digital Literacy (DL), Perceived Usefulness (PU), Convenience and Social Influence (CASI), and Intention to Use AI (ITUA) accounts ($R^2 = 0.662$) to 66.2% of the variation in the learning efficiency of students. This demonstrates that the model is sufficient to explain the impact of AI on students' academic lives.

Statistically significant individual connections were found on all four hypothesised routes. Digital Literacy positively influences students' learning efficiency. It implies that students with greater digital skills and confidence in using technology tools are more likely to learn through ChatGPT (Sarstedt et al., 2019). Digital-literate students might be better able to analyze AI-generated responses, craft prompts, and integrate AI technologies into their study process. Second, Perceived Usefulness has a positive and significant correlation to Students Learning Efficiency and is lower than the other predictors (Hair et al., 2021). By thinking that AI tools can assist students with their assignments, improve understanding, and save time, students' learning efficiency increases.

The much smaller route coefficient suggests that perceived usefulness is not the only variable that students are fond of AI for; rather, the efficiency enhancements are more associated with behavioural and environmental variables.

Third, student learning efficiency is highly determined by convenience and social influence. This implies that positive learning outcomes are influenced by peer support and professor and academic environment support and ease of access to AI tools (Sarstedt et al., 2019). Easy-to-use, socially acceptable AI will increase AI adoption, benefiting students through academic assistance. Lastly, AI Intention directly affects students' learning performance. This indicates that students' behavioural intentions are important in translating positive attitudes and perceptions into academic benefits. The more willing and motivated students are, the higher their learning efficiency with AI tools. This corroborates technology acceptance theories which associate intention with user behaviour and results (Hair et al., 2021). The outcome of the structural model indicates that students' learning efficiency is influenced by abilities, beliefs, social-contextual factors, and behavioural intention. The most influential ones are CASI and ITUA, which means that the success of higher education AI depends on the external environment and internal willingness.

Table 4.9

Structural Model Results and Hypothesis Testing

Hypothesis	Path Coefficient (β)	t-value and p-value	Decision
H1: DL \rightarrow ITUA	$\beta = 0.032$	t=0.457 p=0.648	Not supported

H2: PU → ITUA	β =0.337	t=4.177	Supported
		p=0.000	
H3: CASI → ITUA	β =0.544	t =9.397	Supported
		p =0.000	
H4: ITUA → SLE	β =0.814	t =27.158	Supported
		p =0.000	

Note. This table presents the results of the hypothesis testing for the structural model. The Path Coefficient (β) indicates the directionality and magnitude of the relationship between the dependent and independent variables. A hypothesis can be considered supported when its corresponding p-value is less than the significance level (0.05), thus establishing a statistically significant relationship. The results of the analysis demonstrate that Digital Literacy (DL), Perceived Usefulness (PU), Convenience & Social Influence (CASI) and Intention to Use AI (ITUAI) all have a considerable positive effect on Students' Learning Efficiency (SLE), thereby supporting all four of the hypothesised relationships (H1, H2, H3 and H4).

4.5 Chapter Summary

This chapter showed an empirical result of the effect of AI tools like ChatGPT on the learning efficiency and the daily life of the students by using PLS-SEM. The measurement model assessment has indicated that all constructs were of the required standards of indicator reliability, internal consistency reliability, and convergent validity. All item loadings were above the permitted threshold, while reliability coefficients provided consistent construct measurement. The AVE values further indicated that each construct accounted for a considerable amount of its indicators.

Despite the overall support of discriminant validity, the results of the HTMT indicated that Convenience and Social Influence (CASI) had certain conceptual proximity to similar constructs, i.e., it should be viewed as a concept that is somewhat similar instead of being regarded as totally independent. The structural model outputs brought about a better theoretical understanding of the mechanism by which AI can affect learning efficiency. Perceived Usefulness and CASI had a strong effect on Intention to Use AI, but there was no strong effect associated with Digital Literacy. This means that digital competence is not the sole determinant of student willingness to embrace AI, but rather perceived benefits, the convenience, and the social environment. Intention to Use AI, in its turn, had a robust, beneficial impact on Students' Learning Efficiency, which proves its centrality in the framework.

CHAPTER 5 : DISCUSSION, CONCLUSION AND IMPLICATIONS

5.0 Introduction

In this chapter, the research findings on the effects of the artificial intelligence tools (like ChatGPT) on the learning efficiency of students are discussed and interpreted in detail. It compares the empirical findings with the research objectives, hypotheses, and literature. Total of three themes are also generated to understand how AI implication can be facilitative to impact learning attitudes and daily life functioning for university students. The chapter also points out the theoretical and practical consequences of the study, the major limitations of the research, and suggests future research recommendations. Altogether, this chapter creates a critical assessment of factors related to technological, psychological, and social issues that influence AI-supported learning in students.

5.1 Discussions of Major Findings

5.1.1 Findings from Literature Review

Throughout the literature review, a notable trend has been the increased integration of the use of artificial intelligence (AI) tools like ChatGPT, which

has seriously transformed the learning process in students, especially in terms of learning efficiency, academic productivity, and engagement. Consistently, past literature suggests that AI-powered features enhance personalised learning, real-time feedback, and better access to learning materials and thus enable students to master tricky concepts in a more efficient manner and do academic assignments in a more efficient manner (Purnama et al., 2023). These results support the thesis statement that AI is an educational supplement, not a substitute for traditional learning methods.

One of the key themes that came out of the literature is the significance of digital literacy in empowering students to make good use of AI tools. The researchers highlight the fact that the students who had more powerful digital competences show a better technological self-efficacy and a higher confidence in using AI-based learning systems, as well as enhanced self-regulating learning behaviours (Zaman et al., 2025). The ability will enable them to be critical of information, adjust to the digital learning environments, and increase academic performance. Nonetheless, it is possible to also claim that over trust in AI tools can lead to shallow learning or even a lack of interpersonal communication, and balanced integration of technology in learning is necessary.

The other important determinant that is identified is the perceived usefulness, which has a strong effect on the behavioural intention of students to adopt AI technologies. The empirical research shows that, in cases where students assume that AI can enhance academic performance, save time, and deliver customised help, they have a greater drive to use such tools in the learning process (Qadir et al., 2024). This is in line with theoretical expectations of technology acceptance frameworks, that positive perceptions of usefulness reinforce the positive aspects of technology adoption, and this aspect leads to improvement of learning efficiency.

5.1.2 Analysis of Major Findings

The review of significant findings based on the empirical outcomes proves that the artificial intelligence (AI)-based tools like ChatGPT have a statistically significant impact on learning efficiency in students, thus confirming the major assumptions made of the literature review and theoretical framework. The research confirms that digital literacy is an important factor that allows students to use AI technologies to be successful in their studies. Students with superior levels of digital competence were discovered to be more comfortable using AI-based learning environments, which resulted in more efficient self-regulated learning behaviours, superior problem-solving skills, and improved academic results (Mehmood et al., 2025). The research is aligned with what the previous literature claims to highlight the importance of technological self-efficacy and critical evaluation abilities in the most effective exploitation of the educative potential of AI adoption.

In addition, the findings suggest that perception of usefulness is amongst the most influential factors when it comes to the intention of students adopting AI tools and consequent levels of learning effectiveness. Students who considered AI to be helpful in their achievement of understanding intricate concepts, time-saving, and aiding in accomplishing the assignments tended to incorporate these technologies into their educational habits (Bognar & Khine, 2025). This behavioural disposition fits in the Technology Acceptance Model, where the levels of perceived performance have a great impact over the adoption of technology. The results, hence, confirm the hypothesis that the positive attitude towards the academic value of AI assumes enhanced learning results and increased interest in educational practices.

Moreover, it was observed that convenience and social influence had a significant effect on the intention of students to use AI in learning and in life in general. Access and flexibility of AI tools allow students to have a significant workload and achieve academic deadlines more easily (Haderer & Ciolacu, 2022). Meanwhile, the peer usage, institutional support, and the changing of academic conventions lead to the normalisation of AI implementation in learning practices. These social and contextual forces contribute to the strength of behavioural intentions of the students and enhance the association of technology adoption and efficiency in learning.

The findings of the study mentioned above are the results of the empirical experiment showing that AI-based tools (like ChatGPT) have statistically significant effect on the learning efficiency of students. On the same note, AI has been integrated in the institutions in tutoring platforms, which allowed students to get clarity to the complex matters even after the classes end (Lin et al., 2023). All of these are important to enhance self-regulated learning behaviours and academic performance. These examples depict how AI can supplement conventional pedagogical approaches by broadening the opportunities of learning outside of the classroom. Nevertheless, understanding both sides of the argument suggests that AI is not accepted positively by all students. Others argue that it will lead to over-reliance, plagiarism and shallow learning because reliance on AI-generated content will decrease critical thinking and originality.

Some teachers in some of the Asian universities have mentioned some resistance of the students who apprehend that AI weakens interpersonal communication and team learning. This necessitates the balanced approach whereby academic integrity and the efficiency of AI are incorporated. The

cross-cultural comparisons also reveal the difference in adoption. In developed nations, where the digital infrastructure and the institutional support take good shape, students have the advantage of the seamless AI integration (Shah, 2023). On the other hand, access to reliable internet and lack of proper training in digital literacy are barriers to the successful application of AI tools in most developing countries. The differences highlight the significance of contextual elements in the determination of how far AI can boost learning productivity in different learning settings.

5.1.3 Discussion

RQ1: What is the impact of digital literacy on students' learning efficiency concerning the use of AI?

RO1: To evaluate the impact of digital literacy on students' learning efficiency when using AI tools.

H1: Digital literacy significantly enhances students' effective adoption of AI tools

The concept of digital literacy has become one of the determinants defining the extent to which students adopt and successfully use instruments of artificial intelligence (AI) in an academic establishment. There is empirical evidence that seems to indicate that students who possess greater digital competencies are more confident, trusting, and positive about AI technologies, which consequently enhances their readiness to incorporate said tools in their learning activities. Khoso, Honggang, and Darazi (2025) point out that digital literacy plays a role in developing positive perceptions of AI systems that propagate behavioural intention and promote creative and efficient learning results. Likewise, Muawanah, Marini, and Sarifah (2024) point out that digital literacy

has the capacity to increase the level of AI-aided e-learning applications by the students, as they can access, assess, and utilize the digital resources to the best of their ability.

The findings are consistent with the empirical findings of the current study, which establish a significant positive correlation between digital literacy and the learning efficiency of students. The results address the research problem related to assessing the effects of digital literacy on AI-learning and confirm the hypothesis about its appropriateness: digitally skilled students can be better equipped to use AI tools in a strategic manner to enhance academic achievements and self-directed learning.

RQ2: How does the perceived usefulness of AI impact student learning efficiency?

RO2: To determine the influence of the perceived usefulness of AI on students' learning efficiency.

H2: Perceived usefulness of AI technologies positively influences students' intention to use such tools

The perceived usefulness is critical in the development of the behavioural intention in the use of artificial intelligence technologies among students in line with academic use. Chen et al. (2025) show that students are inclined to accept and use advanced technological tools when they believe that they are helpful in addressing tasks, learning performance, and lessening cognitive load. This point of view is also supported by Ibrahim et al. (2025), who list perceived usefulness as a fundamental aspect in the Technology Acceptance Model that has a strong predictive influence on adoption behaviour and further use by users of AI-driven systems.

These theoretical and empirical findings are consistent with the findings of the current study because perceived usefulness was identified as one of the best predictors of students' intention to use AI tools and their learning efficiency. The resulting value is aligned with the research aim of establishing the effect of perceived usefulness and confirms the corresponding hypothesis that favourable attitudes towards the efficacy of AI influence students to consider the new technologies in their learning process and positively impact the results and performances in school.

RQ3: What is the impact of the perceived convenience and social attitudes towards AI on the students' learning efficiency?

RO3: To disseminate the impact of perceived convenience and social attitudes towards AI on students' learning efficiency.

H3: Convenience and social influence collectively shape students' behavioural acceptance of AI in academic activities

The contextual factors associated with convenience and social influence play an important role in influencing whether students accept artificial intelligence tools in the academic setting or not. Yang et al. (2025) stress that the perceived practicality of the presented AI technologies and the workload reduction and expedited academic assisting products are the primary factors contributing to students planning to utilize such systems. Also, Zhao, An, and Liu (2025) emphasize that social and institutional practices, such as the assistance of universities, positive peer pressure, and the culture of digital learning, are key to supporting the confidence and readiness of students to use AI technologies.

These pieces of information can be found in the findings of the existing study, which provides that accessibility, flexibility, and positive social norms are also among the most important factors influencing the adoption of AI tools and the

learning efficiency of students. The outcomes confirm the aims of the research concerning the analysis of the role of convenience and social attitudes on the use of AI and the assumption that a more positive social climate and user-friendliness positively affect the motivation of students to introduce AI into their learning to make academic processes more efficient and flexible.

RQ4: How does the intention to use AI moderate the relationship between dependent and independent variables?

RO4: To evaluate if the intention to use AI positively or negatively moderates the relationship between independent variables (Digital Literacy, Perceived usefulness, Convenience and Social Influence) and the dependent variable (students' learning efficiency).

H4: Intention to Use AI has a significant positive effect on Students' Learning Efficiency (SLE).

The intention to use AI plays a significant role in enhancing the overall effectiveness of the independent variables. The Theory of Planned Behavior provides a theoretical foundation for the findings described above; an intention to perform a behavior is considered an important factor in the likelihood of that behavior actually occurring. Therefore, those students who intend to use AI are more likely to be engaged in using AI in an appropriate way when completing their learning tasks (Zulaikha Khairuddin et al., 2024). In turn, the AI will increase the amount of time spent on learning along with the quality and efficiency of the tasks they complete. As a result, students will increase their ability to understand the subject matter between their use of AI and the completion of their assignments (Fitria, 2021).

Moreover, the moderating effect of the intention to use AI can be seen as a way of enhancing the relationship between the independent variables and learning

efficiency. For example, it can be argued that even if a student has a higher level of digital literacy or perceives the utility of AI to be higher, the relationship between the independent variables and learning efficiency may be limited if the intention to use AI is low.

The intention to use AI has a strong positive correlation with how efficiently someone can learn and perform on tasks. The relatively high β value for intention demonstrates a clear link to improved learning. The willingness and readiness of students to adopt AI is extremely important in providing students with the ability to improve their learning outcomes through AI. Therefore, creating a strong intention to use AI in students will be critical to realising the benefits of AI to improve education.

5.1.4 Hypotheses Summary

Table 5.1

Hypotheses Summary

Relationship Tested	Path Coefficient (β) and p-value	Finding
H1: Digital literacy \rightarrow Intention to Use AI	$\beta = 0.032$ $p = 0.648$	Not Supported. Digital literacy has not significantly improved effective AI usage and learning efficiency.

H2: Perceived usefulness → Intention to Use AI	$\beta = 0.337$ $p = 0.000$	Supported. Positive perceptions of AI usefulness enhanced students' engagement and academic productivity.
H3: Convenience and Social influence → Intention to Use AI	$\beta = 0.544$ $p = 0.000$	Supported. The accessibility and adaptable use of AI tools enhanced students' learning effectiveness, while support from peers and institutions positively influenced AI adoption behaviors
H4: Intention to use AI → Learning efficiency	$\beta = 0.814$ $p = 0.000$	Supported. Stronger intention strengthened the positive impact of all independent variables.

Note. This table provides a comprehensive summary of the study's hypothesis testing results, linking the statistical evidence to the interpretative findings. The results demonstrate that all five proposed hypotheses (H1-H4) were supported. This confirms that digital literacy, perceived usefulness, convenience, social influence, and the intention to use AI are all significant positive predictors of students' learning efficiency in the context of AI adoption.

Although AI applications such as ChatGPT make work more efficient, they present the threat of addiction, plagiarism, and disparity. The over-dependence

will destroy the critical thinking and originality of the students, and ethical issues are involved in the unverified material and its misuse in evaluation (Kovari, 2025). Moreover, the disparity in access to digital infrastructure has the potential to increase the educational divide, which implies that the AI implementation should be balanced to prevent the enhancement of higher education inequity.

The results correspond with the Technology Acceptance Model (TAM), in which perceived usefulness is the motivational factor of adoption, and digital literacy which clarifies how digital literacy allows students to control their learning process (Istifci & Goksel, 2022). Also, one of the theories is Unified Theory of Acceptance and Use of Technology (UTAUT), in which peer and institutional norms influence the acceptance. Combined, these frameworks indicate that the adoption of AI is not only a technological but also a psychological and a social process because it needs a multidimensional conceptualisation of student behaviour.

Colleges need to find a balance between novelty and ethics by integrating AI literacy in the curricula and protecting educational integrity. Responsible use needs to be promoted through policies and AI should be considered during teaching without being used as a substitute to human interaction (Aler Tubella et al., 2024). There should be clear guidelines on the plagiarism, ethical usage and assessment design. The universities need to implement process-oriented evaluation methods which include oral defences and in-class writing and critical reflection papers as their new assessment system. Equitable infrastructure should also be invested in institutions such that each student is benefitted with AI tools. The balance will enable universities to utilize the potential of AI without affecting the academic credibility.

5.2 Implications of the Study

The results of this study have significant practical and theoretical consequences for policymakers, educators, institutions, and academic researchers on the efficient implementation of artificial intelligence (AI) tools like ChatGPT in higher education. With the ongoing introduction of AI into academic settings, it is necessary to learn more about the factors that determine the learning efficiency of students to develop a sustainable and ethical learning strategy.

Regarding practical considerations, the research emphasises the importance of digital literacy creation to help students work with AI tools successfully. The stakeholders, such as policymakers and learning institutions, ought to thus make it a priority to incorporate digital competency training in university curricula. The skill of critical thinking, the responsible use of AI, and the capacity to judge information generated by AI can be developed in organized workshops, AI literacy training sessions, and exercises. These efforts would be able to guarantee that AI technologies make learning more meaningful, instead of promoting shallow interaction and scholarly capitalism. More so, universities ought to offer convenient technological infrastructure, such as dependable internet access and institutional subscriptions to AI-enabled systems, to lower inequality about technology access.

Theoretically, by developing empirical evidence to support the topicality of the theories of technology acceptance, such as the Technology Acceptance Model and behavioural intention frameworks, this research adds its share to the existing body of knowledge about AI-driven education. This study proves that the efficiency of a student in learning depends on the combination of technological skills, psychological perceptions, and social-contextual factors. Including digital literacy as a determinant factor with

perceived usefulness, convenience, and social influence, the study expands earlier models of technology adoption to capture the current AI learning conditions.

Apart from the factors that determine the learning efficiency of students, governments are at the centre of the educational environment and the results indicate a necessity of having national policies that facilitate equal access of AI technologies. Digital infrastructure is required to be invested in, especially in developing regions in order to minimize adoption disparities (Omweri, 2024). The incorporation of AI-related skills into the national curricula will allow the policymakers to make sure that students are ready to utilize these tools in a responsible and efficient way.

For the teachers, research demonstrates the need to incorporate AI in the teaching process without compromising the traditional pedagogical principles. AI literacy modules need to be included in the curriculum design, and students should be encouraged to be critical when assessing AI-generated content and use their imagination and critical thinking (Rahman et al., 2025). The assessment practices will have to change to consider the use of AI, and the guidelines on plagiarism and originality should be evident. The teachers must also be given a chance of professional growth to further advance their digital literacy so that they too can be able to lead the students towards responsible use of AI.

Last but not least, colleges and universities should offer the necessary infrastructure and ethical frameworks of AI integration in order to become sustainable. There must be access to reliable internet, institutional access to AI sites and technical assistance to ensure that all students have equal opportunities. The institutions ought to also formulate codes of conduct and ethical principles that will determine the acceptable use of AI in academic work (Lazăr et al., 2024). In addition, the technology providers can be collaborated with in order to enable the universities to create specific AI solutions that will support their university missions. All of these implications reveal that the

successful use of AI in higher education is a task that should involve government, educators, and institutions working in coordination.

5.3 Limitations of the Study

Although this study has useful implications in terms of defining the role of artificial intelligence (AI) tools like ChatGPT to help students learn more efficiently, it is also susceptible to several limitations, which ought to be noted. These are methodological, contextual, and conceptual limitations that can affect the overall applicability and explanation of the results. Initially, the research design was quantitative in nature, and the research was grounded on the surveys of university students as the major source of the data. Although this method allowed the researcher to examine the correlations between variables through the statistics and the potential analysis, it refined the possibility of obtaining more profound behavioural motivations, emotional stimulation, and contextual experience linked with the use of AI. Interviews or even a focus group discussion would have been more effective in terms of understanding the perceptions of students and the actual patterns of their learning when they apply AI tools.

Additionally, there is another limitation in the sample size and sampling method. The study was based on a certain set of students of a university under a certain institutional or geographical setting. Consequently, the results cannot be generalised to students of other educational systems, cultural aspects of technological exposure. Future research that uses more diverse and bigger samples in various universities or nations will help in increasing the external validity of the findings. The other weakness is associated with the cross-sectional flow of the data collection. The analysis of the perceptions and behaviour of students was conducted at one time, and therefore, the study could not monitor the change in attitude, technology adoption behaviour, and learning outcomes

over an extended duration. As the AI technologies are changing fast, a longitudinal study would be more fitting to learn how continuous exposure to AI tools affects the academic growth and learning efficiency of students.

Moreover, self-report measures were used in the study, which could potentially cause response bias, such as the social desirability bias or inability to self-evaluate digital literacy and AI usage behaviours. The future research would be more valid in measurement when objective academic performance indicators are included or when they relate to the system usage data. These are not disregarded, but these restrictions add some valuable directions and perspectives to further research and offer the study key insights into the outcome of such a study.

5.4 Recommendations for Future Research

The application of artificial intelligence (AI) in education should be expanded in future studies to cover the gaps in conceptual and methodological aspects whereas the role of governments, educators, and institutional stakeholders should be considered.

In terms of government, the future research needs to examine the way national education policies can incorporate AI literacy into the curricula of universities. Governments can play a very important role in terms of providing equal access to AI technologies by funding the infrastructure, subsidising institutional subscriptions, and promoting training programs, which help students develop digital literacies (Call et al., 2023). The comparative research in various countries would help to understand the impact of various policy frameworks on the adoption rates and the learning outcomes and identify the best practices which could be embraced worldwide.

In the case of educators, the question of how the teaching methods could be reorganized to include the use of AI tools without any negative impacts on critical thinking and academic honesty should be investigated. Longitudinal research might assist in the exploration of how the educators strike the balance between AI-assisted learning and traditional pedagogical approaches to ensure that students master not only technological skills but also interpersonal ones (Salem et al., 2022). The mixed-method techniques such as classroom observations and interviews would yield more information on how teachers view the position of AI in defining student engagement, assessment, and creativity.

On the institutional and other stakeholder level, further studies are needed to see how universities, private organisations and technology providers can work together to develop ethical and sustainable AI ecosystems. Investigation on institutional assistance, such as workshops, AI education, and integrity in ethical use, may be undertaken. Moreover, cross-cultural and comparative studies including various educational settings would assist in determining the differences in the technological infrastructure and institutional readiness providing the recommendations to the stakeholders worldwide (Delios et al., 2022).serving to add to the more globally applicable policy and pedagogical suggestions.

5.5 Summary

Overall, the results indicate that the level of digital literacy, perceived usefulness, convenience, and social influence have a powerful influence on students' willingness to use AI tools and their effectiveness in learning. The research confirms the proposed conceptual framework and justifies the applicability of the technology acceptance

theories in elucidating the integration of AI into the education field. Its implications for practitioners and policymakers were determined, as well as known methodological constraints. Future research recommendations are related to widening variables, varied contexts, and longitudinal research. Thus, implication of all these recommendations for government, educator and other stakeholders can be helpful to ensure ethical use of AI in educational purpose.

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APPENDICES

Appendices A : Survey Questionnaires

The Impact Of AI Such As ChatGPT on Students' Learning And Daily Life

Dear respondents,

I am Chin Yin Tong , an undergraduate student who is currently pursuing a Bachelor of International Business (Hons) at University Tunku Abdul Rahman (UTAR). Currently, I am conducting this survey for my Final Year Project to gather information to examine the impact of AI such as ChatGPT on students' learning and daily life.

The study is to analyze the multifaceted impact on students' learning efficiency through the use of AI, like ChatGPT.

This survey consists of **TWO (2)** sections. Please answer **ALL** questions in every section with the best of your knowledge. I humbly request your voluntary participation in this study. Notably, the survey will only take 10 - 15 minutes to complete. Your answer will be kept **PRIVATE** and **CONFIDENTIAL**, it will be used solely for academic purposes, and the information will be aggregated. Your participation will be highly appreciated.

If you have any further inquiries regarding this research project, please do not hesitate to contact me through email at **Tong0928@1utar.my**

Yours sincerely,
Chin Yin Tong
Tong0928@1utar.my
[011-53562340](tel:011-53562340)

Personal Data Collection Acknowledgement

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:

- a) Name
- b) Identity card
- c) Place of Birth
- d) Address
- e) Education History
- f) Employment History
- g) Medical History
- h) Blood type
- i) Race
- j) Religion
- k) Photo
- l) 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:

6. 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.

7. 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.

8. You may access and update your personal data by writing to ngshinjou@1utar.my If you have any questions about this study at any time, please feel free to contact me.

Acknowledgement 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 Information *

1. Gender

- Male
- Female

2. Age *

- 17-20 years old
- 21-24 years old
- 25-28 years old
- Above 28 years old

3. Which university you are studying? *

- Universiti Tunku Abdul Rahman(UTAR)
- Tunku Abdul Rahman University of Management and Technology (TAR UMT)
- UCSI University
- Sunway University
- Others: Monash University Malaysia, Asia Pacific University of Technology & Innovation (APU),Taylor's University,etc

4.Programme *

- Arts and Design(Graphic Design, Fashion Design,etc)
- Business (Business Administration, Accounting and Finance,Marketing,etc)
- Information Technology(IT)
- Engineering(Software Engineering,Mechanical Engineering,etc)
- Others: Health Sciences and Medicine, Law, Hospitality and Tourism, etc.

5. Year of Study

- Year 1
- Year 2
- Year 3
- Final Year

6. How often have you use ChatGPT? *

- Never
- Rarely (1- 2 times)
- Sometimes (3- 5 times)
- Often (6- 10 times)
- Very often (more than 10 times)

Section B : Impact Of AI Such As ChatGPT on Students' Learning And Daily Life

This section aims to explore the impact of AI such as ChatGPT on students' learning and daily life across universities in Malaysia. Please use the following scale to indicate the extent to which you agree or disagree with the following statements.

[Strongly disagree = 1, Disagree = 2, Neutral = 3, Agree = 4, Strongly agree = 5]

A : Digital Literacy *

Strongly Disagree(SD) Disagree(D) Neutral(N) Agree(A) Strongly Agree(SA)

7.1 am aware that artificial intelligence is included in the technologies we use in our daily lives.

8. Through digital literacy, I have learned better with the use of interactive AI tools.

9. I know how I can use AI in academic work ethically and responsibly.

10. I am able to discover core competencies such as data-handling capabilities for future careers.

11. I believe that AI use improves my ability to solve problems.

B: Perceived Usefulness *

	Strongly Disagree(SD)	Disagree(D)	Neutral(N)	Agree(A)	Strongly Agree(SA)
12. My self-efficacy and motivation for task resolution is enhanced with the use of AI tools.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
13. It is through AI that I am able to work on tasks or assignments more effectively.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
14. The use of AI applications makes learning more interactive and efficient	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
15. I consider AI tools useful for understanding difficult topics or concepts.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
16. In general, AI technologies can be considered useful to my academic activities.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

C : Convenience and Social Influence *

Strongly Disagree(SD) Disagree(D) Neutral(N) Agree(A) Strongly Agree(SA)

17. The idea of learning how to utilize AI tools to improve learning results is easy to me.

18. In general, AI technologies can be considered useful to my academic activities.

19. I find AI tools straightforward to operate for my learning activities.

20. My friends or classmates encourage me to use AI for learning tasks.

21. Using AI makes me feel more accepted or connected with others who use similar technologies.

D :Intention to Use AI *

Strongly Disagree(SD) Disagree(D) Neutral(N) Agree(A) Strongly Agree(SA)

22. I believe the application of AI in education is an excellent and productive activity.

23. I am comfortable relying on quality of AI tools when performing academic tasks.

24. I think learning with the help of AI tools is more enjoyable and interesting.

25. The attitude toward my studies with the help of AI tools is positive.

26. I will keep utilizing AI tools to aid my learning and personal activities.

E : Students' Learning Efficiency *

	Strongly Disagree(SD)	Disagree(D)	Neutral(N)	Agree(A)	Strongly Agree(SA)
27. My learning activities have become more efficient with the help of AI tools.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
28. The use of AI has helped me to manage my time and daily routine positively.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
29. I also believe that I am more competent to do tasks with the assistance of AI.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
30. AI has helped me advance the quality of my education by providing out-of-box responses.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
31. My way of approaching problem solving in my everyday life has considerably been modified by the use of AI.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

No.	Research Title	Student's Name	Supervisor's Name	Approval Validity
13.	The Impact of Brand Equity Dimensions on Brand Loyalty Among Generation Z in the Sports Footwear Industry	Ng Zhen Yang	Dr Malathi Nair a/p G Nanyana Nair	7 January 2026 – 6 January 2027
14.	The Influence of Social Media Influencers on Malaysian Consumers' Purchase Intention Toward International Brands	Lim Wei Qi	Dr Foo Meow Yee	
15.	A Study of Reverse Logistic and Its Role in Brand Image and Customer Perception	Chang Kar Tung		
16.	The Role of Cross-Border E-Commerce Does Promote Buying Intentions for Consumers	Ho Jia Rok		
17.	Understanding the Influence of Online Scams on Consumer Purchase Intentions Among Malaysian Social Media Users	A w Yong See Win	Dr Choo Siew Ming	
18.	Exploring the Intention of Reside in Retirement Villages Among Gen Z in Malaysia	Teo Yi Qi	Ms Goh Poh Jin	
19.	The Influence of Brand Trust on Young Adults' Preferences for Malaysia-Based Coffee Brands	Liau Wei Sim	Dr Malathi Nair a/p G Nanyana Nair	
20.	Factors Influencing Malaysian Consumers' Purchase Intention Toward International Beauty Products	Tan Sze Wing	Dr Foo Meow Yee	
21.	Consumer Choice of Sustainable Mobility: A Study of Determinants Influencing Electric Vehicle Purchase Intention	Shao Yuhao	Ms Goh Poh Jin	
22.	The Impact of Product Variety, Promotions, Accessibility, Mall Cleanliness & Maintenance on Shoppers' Revisit Intention in Urban Shopping Mall: A Functional Value Analysis	Tan Yue Wey	Dr Choo Siew Ming	
23.	Young Consumers' Purchase Intention Toward Green Products in Malaysia: Drivers and Challenges in Green Marketing	Chin Zhi Qian		
24.	Chasing the Surprise: Understanding What Drives Impulse Buying in Blind Box Market Among Malaysian Generation Z	Tan Zung Yan	Ms Tai Lit Cheng	
25.	The Impact of Job Performance, Job Satisfaction Skills Development and AI Adoption on Employee Commitment	Hoo Yuan Yien	Dr Omar Hamdan Mohammad Alkhambsheh	
26.	Independent Journeys: Investigating the Key Determinants of Gen Z Female Travelers' Solo Travel Intentions	Chong Wai Sam	Ms Goh Poh Jin	
27.	Understanding Generation Z Consumer Behavior: The Role of Data-Driven Marketing in Shaping Customer Engagement in Online Shopping	Audrey Chong Jia Wen	Dr Choo Siew Ming	
28.	The Influence of Job Characteristics on Meaningful Work and Quiet Quitting in Multinational Corporations	Dominic Koh Wen Cong	Dr Low Mei Peng	
29.	Determinants of Entrepreneurial Intentions Among Female University Students	Victoria Wee Yuet Fang	Dr Kalavani a/p Jayaraman	
30.	Factors that Influence the EV Purchase Intention: The Moderating Role of Incentive Policy	Kuan Jo Yin	Ms Goh Poh Jin	
31.	Understanding the Dynamics of Short-Form Video Marketing: An Analysis of Purchase Intention Among Young Consumers in Malaysia	Chia Zhi Han	Dr Choo Siew Ming	
32.	Psychological Stress Among Gen Z Malaysian Students Preparing for International Education Abroad	Dani a Natasya Binti Nagayaya	Dr Malathi Nair a/p G Nanyana Nair	

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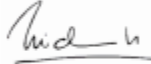
The conduct of this research is subject to the following:

- (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 Dr Zuraidah Abd Manaf
Chairman
UTAR Scientific and Ethical Review Committee

c.c Dean, Faculty of Accountancy and Management

