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Drivers of the use of AI-powered tools in academic research:

A study of university students in South Africa

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A research report submitted to the Faculty of Commerce, Law and Management, University of the Witwatersrand, in partial fulfilment of the requirements for the degree of Master of Management in the field of Digital Business

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ABSTRACT

The integration of Artificial Intelligence (AI) across various sectors, including education, has garnered significant attention due to its potential to enhance productivity, accuracy, and innovation. There has been a notable lack of research focusing on students' adoption of AI tools in research settings, within the context of South Africa. The primary objective of this study was to provide insights to inform strategies aimed at facilitating the effective implementation of AI-powered technologies within the academic research landscape.

The study employed a theoretical framework grounded in the Technology Acceptance Model (TAM), which provides a foundation for understanding individuals' acceptance or rejection of technology. The study aimed to investigate the drivers influencing university students' utilisation of AI tools in educational research settings. Adopting a positivist research philosophy, the study utilised a quantitative research design as the primary inquiry strategy. This involved the administration of a research survey to collect and analyse numerical data, enabling the testing of hypotheses, identification of patterns, and quantification of relationships between variables. The study employed a cross-sectional time horizon and utilised convenience sampling to administer a survey questionnaire to 271 final-year undergraduate and postgraduate students at Witwatersrand University.

Analysis of the collected data using descriptive and inferential statistics revealed several key findings. A positive attitude towards utilising AI tools was found to be driven by perceived usefulness, perceived ease of use, prior knowledge, and awareness about the tools. This relationship was moderated by factors such as trust and self-efficacy. The AI tools were primarily utilised for tasks such as searching and summarising articles, writing, editing grammar, and making unbiased judgments about articles. Importantly, students were influenced by the perceived benefits derived from using specific AI tools, and the ease of use associated with these tools.

This research study findings suggest that promoting awareness of AI tools among university students has the potential to enhance research outcomes, improve scholarly efficiency and increase overall effectiveness. As the demand for AI technologies continues to grow, integrating them into higher education settings holds promise for unlocking substantial benefits and transforming the academic research landscape.

KEYWORDS: Artificial Intelligence, Technology Acceptance Model, Perceived Usefulness, Perceived Ease of Use, Perceived Information Effectiveness, Social Influence, Prior Knowledge and Awareness, Trust, Self-efficacy

DECLARATION

I, Danisile Priscilla Ngomane, declare that this research report is my work except as indicated in the references and acknowledgements. It is submitted in partial fulfilment of the requirements for the degree of Master of Management in the field of Digital Business at the University of the Witwatersrand, Johannesburg. It has not been submitted before for any degree or examination in this or any other university.

Name: Danisile Priscilla Ngomane Signature: 

Signed at Johannesburg

On the 20th day of June 2024.

DEDICATION

This research report is dedicated to my daughter, Phakade Ntando Yandisa Ngomane, and my family. Thank you for your support and for allowing me to chase my dreams.

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My daughter, Phakade Ntando Yandisa, I am thankful for your patience and understanding during this phase of my life. You have encouraged me not to give up, as that would have indicated how to deal with difficulties in life. Thank you for staying exceptional in sports and schoolwork during this time.

I want to thank all my friends and colleagues for their support and patience when I was physically and mentally absent.

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LIST OF ACRONYMS

Acronym	Description
AI	Artificial Intelligence
DOI	Diffusion of Innovation
IDT	Innovation Diffusion Theory
NLP	Natural Language Processing
PE	Perceived Ease of Use
PIIT	Personal Innovativeness in Information Technology
SDT	Self Determination Theory
TAM	Technology Acceptance Model
UTAUT	Unified Theory of Acceptance and Use of Technology

CHAPTER 1. INTRODUCTION

1.1 Statement of purpose

This quantitative study sought to explore and analyse the underlying factors driving the utilisation of AI-powered tools in academic research among university students in South Africa.

1.2 Background of the study

This research study is situated within the rapidly evolving landscape of technological advancement, where Artificial Intelligence (AI) plays a pivotal role across various sectors, including education. García-Martínez et al. (2023) highlight this transformation, emphasising AI's potential to revolutionise domains such as politics, economics, education, and social interactions. As technology shapes societal dynamics, adopting AI-powered tools becomes increasingly significant, offering opportunities for enhanced productivity, efficiency, and innovation (Halili, 2019).

Artificial Intelligence, as defined by Wang et al. (2016), encompasses a machine's capacity to perform cognitive tasks akin to human intellect. Its integration has led to significant economic advancements, data management, and computational capabilities (Walton & Nayak, 2021). Leveraging machine learning and deep learning algorithms, AI systems can autonomously identify patterns within datasets and improve over time through self-learning mechanisms (Zhai et al., 2020).

In the context of academia, AI's influence is profound, with universities worldwide emerging as prominent users of AI tools (McCormick & Hall, 2022). This trend reflects a multidisciplinary approach, as observed by Wang et al. (2016), encompassing fields such as computer science, mathematics, psychology, and linguistics. AI's application in academia extends to diverse areas, including scientific research, innovation, and pedagogical practices (Shao et al., 2022).

Holmes et al. (2023) argue that AI can revolutionise academic performance by enabling sophisticated data analysis, simulation generation, and effective communication of findings. The evolution of AI into a "humanised" realm, characterised by increased investment and technological advancements, underscores its transformative impact on various industries, including education (Holmes et al., 2023; Zhai et al., 2020).

Despite the widespread adoption of AI globally and its potential benefits, there is limited exploration of its utilisation and its effects on university students, especially within developing economies such as South Africa. While several studies have examined AI's influence on higher education systems globally, there is a noticeable gap in understanding the drivers of university students' use of AI tools in specific country contexts(Ouyang et al., 2022). By focusing on South Africa, this study seeks to address this gap and contribute to a deeper understanding of the factors influencing AI tool adoption among university students in developing economies.

1.3 Context of the study

The study is premised within the South African context. Data-driven technologies, such as AI, are increasingly being utilised in all aspects of South African lives (Adams et al., 2020). From private companies to non-profit organisations and government agencies, the interest in data-driven models and systems for improving planning, decision-making, and service delivery is steadily increasing, driven by global digitalisation trends and the perceived competitive advantage such technologies offer (Adams et al., 2020).

Based on a survey of the general comprehension of technology associated with the "Fourth Industrial Revolution" (4IR), it was revealed that 39% of South Africans are familiar with AI (Adams et al., 2020). This suggests that there is some awareness of AI technologies in South Africa.

As highlighted by Statista (2023), the percentage of South Africa's overall population using the internet was close to 80% in 2022, and it is projected to reach 90% by 2027, marking an increase of 28% from 2018, when the percentage of the population accessing the internet in the country was 62%. The availability of high-speed internet services to citizens, households, and consumers is crucial to a country's economic development and success. Access to broadband technologies can increase productivity and contribute to economic growth, ultimately decreasing poverty levels in a nation (Mhlanga & Beneke, 2021).

Most South African universities offer public internet access to students, and there is a growing trend of students using cell phones to connect to the internet. Some students come from households with internet connections (Oyedemi, 2015). This suggests that students can access any online technology that is available for use.

Several studies focusing on AI implementations and transformation from institutional perspectives are primarily based in Asian, European, and American contexts (Pedro et al., 2019; Romero & Ventura, 2013; Sitthipon et al., 2022; Wang, 2020). There is limited coverage of such studies within the South African context. This study was done within the context of several AI tools that students in their academic journeys may utilise, and some of them are discussed below:

i. Conversational chatbots

Conversational chatbots are software applications utilising Natural Language Processing (NLP) to imitate human conversations (Pillai & Sivathanu, 2020). Sheehan et al. (2020) state that chatbots are automated advisors assisting individuals in decision-making. A chatbot is a computer software to which one may speak in ordinary human language and have a back-and-forth discussion (Kooli, 2023). Advanced backend systems provide support for chatbot interactions, simplifying the experience for end users (Wang et al., 2022). Using digital intelligent assistants and chatbots benefits sales, marketing, and customer support by enabling conversational capabilities (Sitthipon et al., 2022). Through machine learning and

intelligent software algorithms, these chatbots can engage in more interactive and conversational exchanges with clients (Malik et al., 2021).

ii. Generative AI

Various large-scale NLP AI-powered chatbots utilise machine learning techniques, such as ChatGPT, Bing, and Google Bard, to understand and generate human-like language (Lund et al., 2023).

The AI-powered chatbots can converse with users on various topics, ranging from casual small talk to complex technical discussions (Wardat et al., 2023). Through extensive pre-training on vast data, Wardat et al. (2023) mentioned that these models can generate coherent and contextually relevant responses to user inputs. In educational settings, ChatGPT, for example, can be utilised to offer individualised learning opportunities to students, as it can answer questions, provide explanations, and offer feedback on assignments and tests (Biswas, 2023).

iii. Paraphrasing Tools

Several helpful AI-powered tools are available to assist users with paraphrasing and rewriting text. These tools include Quillbot, Grammarly, and ChatGPT. Their primary purpose is to improve writing clarity, reduce plagiarism, and enhance writing fluency (Nurmayanti & Suryadi, 2023). These tools are utilised for paraphrasing and summarising tasks for students, language translation services, writing assistance, correcting grammar and supporting research and academic writing by generating alternative phrasings and rewording complex sentences (Dewi, 2022; Nurmayanti & Suryadi, 2023). Dewi (2022) posits that students utilise these tools for proofreading their essays and assignments, detecting plagiarism, assisting learners in improving their writing skills, and providing feedback and editing support.

iv. Literature Mapping Tools

Literature mapping tools such as Litmaps and Scite are helpful to researchers as they navigate through a large amount of academic literature and improve their research process. These tools use AI to assist researchers in exploring and visualising

connections between research papers, identifying essential concepts and trends, and finding relevant sources for their studies (Rojas-Sánchez et al., 2023). These tools can help researchers to organise and synthesise scholarly information. They enable researchers to create comprehensive literature reviews, identify research gaps, and gain insights into the existing knowledge in their field (Khalil et al., 2022). Using these tools, researchers can simplify their literature search, discover influential works, and keep updated with the latest advancements in their respective fields (Gasparini et al., 2022). Literature mapping tools facilitate efficient knowledge acquisition and critical analysis and support informed decision-making in academic research (Wagner et al., 2022).

1.4 Research problem

Artificial Intelligence tools are generating an increased interest in tertiary education (Henderson, 2020). In 2019, the Council of Europe's Committee of Ministers adopted a recommendation on digital citizenship education. A key focus was the application of AI in educational contexts (Jokubauskas & Swierczynski, 2020). Despite its recent history, AI is increasingly being introduced into the classroom through various modalities to improve students' achievements (Martínez et al., 2023). Artificial Intelligence is used to improve student learning and skill acquisition beyond traditional classroom settings (Wang et al., 2021). Although incorporating AI into the educational system has been viewed as an efficient mechanism for capacity building, researchers have noticed notable variations in what drives the adoption in the educational context (Al Shamsi et al., 2022).

Adoption of AI is still in the early stages, especially in developing countries and the growth in adoption is expected to increase (Malik et al., 2021). The solution to this challenge hinges on the initial understanding of the drivers of AI usage or lack thereof, as it is seen in the study that was conducted on the use of AI-based voice assistants in an education setting (Al Shamsi et al., 2022). However, research in this area is still limited, creating a paucity of scientific understanding of the drivers of AI tool utilisation (Malik et al., 2021). The University of Witwatersrand, like other universities around

the world, has integrated AI into some aspects of student learning, from classroom lectures to assignment writing (Witwatersrand, 2023). However, ever since the introduction of several AI tools that are commercially available, limited research has focused on addressing the drivers of the adoption of these tools (Al Shamsi et al., 2022; Cubric, 2020). In the context of this research gap, this study examines what drives students to use AI-powered tools, focused on those doing academic research. Furthermore, there is a gap in the body of knowledge on AI studies based in the South African context.

The overarching goal of this study is to comprehensively examine the factors driving university students' utilisation of AI-powered tools in the context of academic research, with a specific focus on the South African setting. To achieve this goal, the research will be guided by several research questions, including but not limited to: What are the primary drivers influencing students' adoption of AI tools in academic research? How do students perceive the usefulness and ease of use of AI-powered tools? What role do prior knowledge and awareness play in students' decision to use AI tools? By addressing these research questions, the study aims to contribute to the existing knowledge on AI adoption in educational contexts, particularly within the South African higher education landscape. The findings of this research are expected to have theoretical implications by advancing our understanding of the factors influencing technology adoption in academic settings. Furthermore, the practical implications of this study are significant, as insights gained can inform educators, policymakers, and technology developers on strategies to promote the effective integration of AI tools into the educational process, ultimately enhancing student learning outcomes and academic performance.

1.5 Research questions

This research seeks to answer the following pertinent questions:

i. What are the critical drivers of university students' use of AI-powered tools?

ii. What is the impact of perceived usefulness and ease of use on the adoption of AI-powered tools?
iii. What is the impact of students' prior knowledge and awareness on AI tool usage?
iv. To what extent do students' perceptions of AI-generated information influence their attitude towards using AI tools?

1.6 Rationale

This study aimed to understand how students have responded to the AI phenomenon in South Africa. It was essential to empirically test what makes students use these tools even though the university does not offer them. Therefore, the Technology Acceptance Model (TAM) was utilised with extensions such as social influence, prior knowledge and awareness, perceived effectiveness of information, trust, and self-efficacy as moderators to understand these drivers. The TAM framework suggests that individuals' intention to use technology is influenced by their perceived usefulness and ease of use (Davis, 1989). By applying this framework, the study aimed to identify the factors driving students' acceptance and utilisation of AI tools. The results of this research study will be valuable in informing educational strategies and interventions aimed at effectively integrating AI tools into learning, improving learning, and assisting in research.

Furthermore, this study sought to contribute to a broader understanding of technology acceptance and usage behaviour in educational settings, building upon prior research by (Alabi et al., 2022; Cubric, 2020). This research added local findings to the pool of international studies on AI adoption by extending current knowledge on student adoption of AI tools. From an educational point of view, the implications of this research are significant. By gaining insight into the critical drivers of university students' use of AI tools, academic institutions, particularly those in South Africa, would be better equipped to understand this phenomenon. This understanding can inform the development of targeted strategies and interventions to promote the effective use of AI tools, thereby enhancing students' learning capabilities.

1.7 Delimitations of the study

The study included students from the University of Witwatersrand in South Africa conducting research. The targeted population was students in the final year of undergraduate studies and onward.

The TAM theory was a foundational theoretical model to explain and predict research students' acceptance of AI-powered tools. This was done with the aid of other extensions such as prior knowledge and awareness, perceived information effectiveness and social influence.

The study is based on the positivist paradigm, which explains behaviour through objective facts, as Park et al. (2020) mentioned. The quantitative research design was adopted as the research strategy.

1.8 Definitions of terms

Artificial Intelligence refers to the ability of machines to carry out cognitive processes typically linked to human intelligence, such as acquiring knowledge, communicating, and resolving problems (Nilsson, 1971).

Machine learning focuses on teaching computers to learn from data without being explicitly taught. The technique enables machines to improve at a task through data-driven learning rather than explicit programming (Mitchell, 1997).

Deep learning is a discipline of machine learning concerned with creating and implementing artificial and intense neural networks (Mitchell, 1997).

Academic performance refers to an individual's level of achievement or success in educational settings, typically measured by various indicators such as grades, test scores, and overall educational outcomes (Rodriguez, 2021).

Tools (technology tools) refer to software, applications, and platforms. AI-powered tools are the software, applications, and platforms infused with AI capability (Neumann et al., 2021).

Academic research is systematic and creative work to increase the body of knowledge. It involves collecting, organising, examining, and analysing scholarly sources to investigate what is known about any topic and contributing new findings based on the research study (Dergaa et al., 2023).

1.9 Assumptions

The study makes use of the following assumptions.

i. Students at Witwatersrand University in South Africa have access to AI-powered tools.
ii. Students at Witwatersrand University in South Africa are using AI-powered tools.
iii. Students at Witwatersrand University in South Africa have access to the Internet.
iv. The participants' responses are a true reflection of their experiences and perceptions.

1.10 Chapter outline

Chapter One introduces the research study, outlining its objectives and the questions it seeks to address. Chapter Two probes into existing literature surrounding the adoption of AI tools by students, offering a comprehensive review of previous studies in the field. In Chapter Three, the methodology employed in this study is outlined in detail, including the research design, data collection methods, and analytical techniques utilised. Chapter Four presents the findings obtained from the research, offering insights into the key drivers influencing students' use of AI tools. Chapter Five critically examines these findings about the existing body of literature, highlighting

similarities, differences, and areas for further investigation. Finally, Chapter Six concludes the study by summarising the research questions, synthesising the key findings, and providing recommendations for future research and practice in AI adoption among students.

CHAPTER 2. LITERATURE REVIEW

2.1 Introduction

This chapter reviews the theoretical and empirical literature that underlies the drivers of using technology and AI-powered tools. The definition of terms, empirical findings from other studies, and formulation of hypotheses and theories used in different studies will be discussed.

2.2 Theoretical Frameworks

The following sections discuss the theories that helped to study the adoption of technology and AI and how different authors adopted the theories. Several theories and models facilitate understanding individuals' acceptance or rejection of technology. The TAM (TAM) is prominent among these models, which draws from fundamental behavioural and motivational theories such as the Unified Theory of Acceptance and Use of Technology (UTAUT), Innovation Diffusion Theory, and Self-Determination Theory. These models have been extensively used to investigate attitudes and behavioural intentions towards adopting educational technology (Kemp et al., 2019; Oyetade et al., 2020).

2.2.1 *Unified Theory of Acceptance and Use of Technology*

The UTAUT was developed based on an extensive review of previous studies on technology acceptance and usage (Venkatesh et al., 2003). This model aims to clarify the elements that impact a user's decision to adopt and use an information system. UTAUT includes four main components: performance expectancy, effort expectancy, social influence, and facilitating conditions, which forecast a user's behavioural intentions and actual use of the technology. These predictors are also impacted by three moderating factors: gender, age, and experience. The unified Theory of Acceptance and Use of Technology is widely acknowledged as one of the most commonly utilised model for evaluating technology acceptance (Blut et al., 2021).

Unified Theory of Acceptance and Use of Technology suggests that the actual use of technology is determined by behavioural intention.

The UTAUT has been applied in various business areas to examine technology acceptance in an organisational and non-organisational context. Palau-Saumell et al. (2019) applied the UTAUT theory to assess the user acceptance of mobile apps for restaurants. In the studies that focused on customer technology acceptance and use by Nikolopoulou et al. (2020) and Tamilmani et al. (2019), they applied UTAUT2, which extended UTAUT with hedonic motivation, price value, and habit behaviour constructs, moderated by age, gender, and experience. In the studies by Al-Adwan et al. (2022) and Wan et al. (2020), the UTAUT was expanded by including endogenous characteristics such as satisfaction and continuous desire to use. De Witte et al. (2021) expanded on UTAUT by including new contextual and moderating factors such as culture, ethnicity, religion as per Hasan et al. (2022), occupation, language, income, education, and geographical location (Dasgupta & Gupta, 2019). These studies highlight the versatility and adaptability of the UTAUT model in numerous domains and the significance of adding additional elements to improve its predictive power and applicability in various scenarios.

Gansser and Reich (2021) applied the UTAUT2 model in the AI adoption studies. Andrews et al. (2021), Chatterjee, Rana, Khorana, et al. (2021) and Ragheb et al. (2022) utilised the UTAUT model without facilitating condition as an independent construct. Chatterjee, Rana, Khorana, et al. (2021) further modified the UTAUT model with external variables such as compatibility as per Marinković et al. (2020), quality, and satisfaction (Wan et al., 2020). In the AI in education study, Raffaghelli et al. (2022) extended the UTAUT model with trust (Wanner et al., 2022). This further suggests that the UTAUT model can be adjusted and extended to suit specific research objectives.

2.2.2 *Innovation Diffusion Theory*

The Innovation Diffusion Theory (IDT) was founded by Everett M. Rogers in 1962 (Rogers, 2010). The IDT posits that innovative individuals tend to be more receptive

to adopting innovative ideas and are better equipped to navigate high levels of uncertainty when considering the purchase of new products or services as they become available in the market (Rogers, 1995). Additionally, personality traits play a significant role in influencing this internal motivation. According to Rogers (1995), for an innovation to gain widespread acceptance, it must possess several key characteristics, including relative benefit, compatibility, complexity, observability, and trialability. These attributes contribute to the ease with which innovations can be adopted and diffused throughout a population. They determine how well the innovation aligns with individuals' needs and preferences, its compatibility with existing practices and technologies, the degree of complexity involved in its adoption, its visibility or observability, and the opportunity for individuals to trial or experiment with it before fully committing. These factors influence the rate and extent to which innovations are embraced and integrated into society. Relative advantage refers to how much better a consumer thinks a new technology is compared to similar existing technologies. Compatibility is how well the consumer feels the new technology fits into their lifestyle. Complexity refers to how difficult it is for the consumer to use the technology. The offer of a trial period before making a financial commitment significantly increases the adoption rates of a technology. Trialability reduces the consumer's perception of risk. Observability refers to the extent to which potential consumers can see technology and its positive effects in action (Rogers, 1995).

Innovation Diffusion Theory was applied by Pinho et al. (2021) to study the factors influencing the use of Moodle as a Learning Management System (LMS) in the academic context. The IDT theory was applied to assess the characteristics of LMS, Personal Innovativeness in Information Technology (PIIT) and frequency of use of the platforms. The results affirmed the theory of IDT by suggesting that PIIT and the characteristics of the new IT contribute to the acceptance and utilisation of the technology (Pinho et al., 2021; Wu & Yu, 2022). Sun and Ting (2019) suggested that IDT needs to be extended with factors from other models, such as perceived ease of use when studying consumer information technology adoption behaviour such as m-commerce.

In AI context, Butt et al. (2021) applied the perceived relative advantage and compatibility dimension of IDT to extend TAM and flow theory to study the adoption of AI-powered AVATAR. Furthermore, Mariani et al. (2022) combined the elements of the TAM, Diffusion of Innovations (DOI), and UTAUT to investigate individuals' acceptance of biometric identification. Lai et al. (2018) combined IDT with the Technology Organisation Environment (TOE) framework to assess the intentions to adopt Big Data Analytics. Alhumaid et al. (2023) further suggested that the key critical components in adopting new technologies at the institutional and social levels are perceived by IDT and TAU.

Innovation Diffusion Theory remains a valuable tool for researchers seeking to understand the factors that influence the adoption and diffusion of innovations through consideration of the characteristics of the innovation and the individual's motivations and perceptions. However, based on the analysis of IDT in the AI context, it can be noted that more insights can be derived when the model is combined with other theories.

2.2.3 *Self Determination Theory*

The Self-Determination Theory (SDT) offers a robust theoretical framework for understanding motivation in educational settings, with profound implications for classroom practices and policies (Ryan & Deci, 2020). The theory posits that self-initiated behaviour and engagement stem from three fundamental psychological needs: autonomy, relatedness, and competence (Ryan & Deci, 2020). Teachers can foster student engagement and participation when these needs are effectively met. As students' fundamental needs are satisfied, their motivational orientation can progress along a continuum from extrinsic to intrinsic motivation, culminating in the internalisation of motivation towards the activity (Xia et al., 2022). This continuum encompasses various stages: motivation, external regulation, introduced regulation, identified regulation, and integrated regulation (Schneider et al., 2018).

The sustenance of students' personal development and well-being hinges on this intrinsic motivation, which has the potential to yield improved academic outcomes.

Consequently, regardless of their initial motivational orientation, students are more likely to exhibit intrinsic motivation to learn when teaching and learning environments effectively address their autonomy, competence, and relatedness needs.

2.2.4 *Technology Acceptance Model*

The TAM is a widely recognised theoretical framework for understanding individuals' acceptance and adoption of technology (Yucel & Gulbahar, 2013). According to TAM, technology adoption is predicted by users' behavioural intention in executing the job and perceived ease of use (Davis, 1989). The technology Acceptance Model posits that these factors influence attitude (A) toward using the system, which impacts individuals' behavioural intention to adopt and use the technology (Mokhtar et al., 2018).

The TAM was extended with security and privacy to study the impact of trust and perceived risks on the adoption of internet banking in India, as well as the intention to use e-health and the adoption of digital payment (Carlos Roca et al., 2009; Kesharwani & Bisht, 2012; Najib & Fahma, 2020; Purwanto & Budiman, 2020). Obaid (2021) integrated TAM with the theory of planned behaviour and extended the model with trust and perceived risk in a study of mobile banking adoption. Trust and dangers seem to be critical factors in studies related to financial systems. In the studies by Lazim et al. (2021), Alfadda and Mahdi (2021), and Al-Qaysi et al. (2020) in the educational and social media context, the TAM model was applied without extension. Alharbi and Drew (2014) extended TAM with a lack of system availability, prior usage experience, and job relevance to study the behavioural intention to use a Learning Management System.

In the study by Chatterjee, Rana, Dwivedi, et al. (2021), the TAM model was combined with a TOE framework to identify factors influencing the adoption of AI in manufacturing and production firms. Mohr and Kühl (2021) and Choe et al. (2022) applied TAM combined with the theory of planned behaviour to learn the behavioural factors influencing the acceptance of AI. TAM was integrated with the perceived contingency model in the study by Lim and Zhang (2022) on AI-driven personalisation

on digital news platforms. Al Shamsi et al. (2022) assessed the adoption of AI-based voice assistants using TAM. They extended it with the subjective norm, enjoyment, facilitating conditions, trust, and security to understand the student's use of AI-based voice assistants for instructional purposes.

Although TAM is the most used model, it has limitations since previous authors mainly extended it with other factors to better understand a particular study. By applying TAM in this study, the aim is to gain insight into how university students perceive the usefulness and ease of use of AI tools and how these perceptions impact the adoption. The model was extended with factors such as prior knowledge and awareness, perceived effectiveness of information, social influence, and trust and self-efficacy as moderators (Venkatesh, 2022).

The acceptance and usage perceptions of technology and AI tools are vital in determining the effectiveness and efficiency of AI tools. Models emphasise the importance of perceived utility, the convenience of use, the fulfilment of psychological needs, and a variety of contextual factors in influencing users' acceptance and adoption of AI technology in educational contexts (Ryan & Deci, 2020; Venkatesh et al., 2003; Yucel & Gulbahar, 2013).

TAM can provide valuable insights into the context of AI tools and their use by students. It can help assess the students' perceptions of how useful AI tools are for their academic tasks (Al-Adwan et al., 2023). TAM can also gauge students' perception of the ease of using AI tools, including interface usability, accessibility, and user-friendliness (Al-Adwan et al., 2023).

Furthermore, students' attitudes to using AI tools can be measured to assess the correlation with actual usage. Like several studies that combined the TAM with other frameworks to achieve the intended objectives, in this study, the TAM was extended to allow investigation of the relationships between the variables that lead to adoption.

2.3 Empirical Studies

This section provides an overview of prior research conducted on artificial intelligence (AI) tools within educational contexts, explaining both the advantages and challenges inherent in their utilisation and adoption within this domain.

2.3.1 *Artificial Intelligence (AI)*

Artificial Intelligence technologies have been viewed as disruptive advancements with the potential to transform academia and scholarly publishing (Lund et al., 2023). Usually, AI capability is presented as chatbots and computer programs that simulate human speech, and this is one example of how these technologies might be used (Kooli, 2023). Chatbots are created using NLP methods, which allow them to read and interpret human language input (Lund et al., 2023).

AI has the potential to alter many industries, including education. AI is any theory, method, or strategy that supports machines, particularly computers, in analysing, replicating, exploiting, and emulating human cognitive processes and behaviours (Lu, 2019; Lund et al., 2023). The key to AI is self-learning by allowing the system to acquire new information and improve its knowledge-based judgements and conclusions through available data (Lu, 2019; Sáiz-Manzanares et al., 2023). This is important in ensuring that there is adaptation capacity and that information is current in the system (Mintz & Brodie, 2019).

2.3.2 *AI tools in academic research*

Many NLP conversational assistants are voice, text, and multimodal assistants' students utilise for their research tasks. A crucial application of AI in educational settings is to enable personalised learning by providing learning guidance, support, and additional materials to students based on their learning status (Hwang & Chen, 2023). The AI tools can go further by summarising learning information and displaying problem-solving or artwork production like an expert teacher (Ahmad et al., 2022). A researcher is expected to go through many articles, and AI tools such as generative

AI can handle large volumes of textual data in a short period, scanning papers and extracting critical information, thus saving researchers time and effort (Dergaa et al., 2023).

Previously, AI technologies were incorporated into applications to improve learners' capacities in memorising, comprehending, applying, evaluating, and assessing (Chatterjee & Bhattacharjee, 2020; Sáiz-Manzanares et al., 2023). Using AI-enabled systems facilitates real-time discussion of searches and problems students may have throughout their learning processes (Li, 2023).

Li (2023) mentioned that students who used the Yixue Squirrel AI adaptive learning system performed better than those who used traditional classroom instruction provided by expert teachers and other adaptive learning platforms. Therefore, students are motivated to adopt AI technologies, as they are expected to assist by catering to the various needs of students, teachers, and researchers (Chatterjee & Bhattacharjee, 2020). As Cox et al. (2019) suggested, AI-powered libraries can improve learning experiences in higher education institutions.

The efficient use of AI in educational settings results in a shift in the whole government's stance regarding the usage of these technologies (Almaiah et al., 2022). With the arrival of AI in education, teachers can be encouraged to reconsider their teaching approaches by presenting assignments that need critical thinking and problem-solving talents that go beyond the actual capabilities of AI that will advance, most likely in an everlasting race with humans (Dergaa et al., 2023).

2.3.3 *Benefits of AI tools in academic research*

AI tools can help develop learning capabilities such as self-reflection, answering complex questions, problem-solving, and making choices (Almaiah et al., 2022). This significantly impacts learning achievements, domains, and methods (Chatterjee & Bhattacharjee, 2020).

Enhancing education quality is a priority in developed and developing countries. AI technologies can be critical in achieving fairness and resolving educational inequality

issues (Chatterjee & Bhattacharjee, 2020; Cox, 2021). Learning with the help of AI has been found to always be better than with traditional methods. Therefore, stakeholders are motivated to adopt AI technologies (Kuleto et al., 2021). However, there is a chance that high-income countries and privileged researchers will soon find ways to exploit AI in ways that accelerate their research and widen inequalities even more (Dergaa et al., 2023; van Dis et al., 2023).

Thorp (2023) suggested that the benefit of using AI-powered tools in academic research is the creation of summaries because a trained AI tool can automatically generate summaries for an article. Furthermore, these AI tools can generate potential research questions on a particular topic (Thorp, 2023). Dergaa et al. (2023) suggested that using such tools with other research methods can provide immediate answers to students outside of traditional methods, helping them search for online study resources and know their results quickly and conveniently.

AI may successfully reduce teacher workloads while also causing a revolution in evaluation methods, resulting in rich improvements in the intelligent tutoring system (Kuleto et al., 2021; Sitthipon et al., 2022). Almaiah et al. (2022) further suggested that using AI to create an intelligent tutoring system may positively affect learning different language skills and enhance learning new vocabulary and pronunciation. As Ragheb et al. (2022) suggested, AI in education promises to significantly impact learning success and student satisfaction.

2.3.4 *Challenges introduced by AI*

Ragheb et al. (2022) mentioned that private universities are more prone to adopting technology in education due to the availability of resources. There are various concerns regarding how generative AI, such as ChatGPT, may affect education, particularly academic writing. Although these AI tools can generate essays on various topics, academic writing still requires improvement (Dergaa et al., 2023). Furthermore, there is a risk that AI-generated information has the potential to infiltrate scholarly articles, negatively impacting the authenticity and credibility of research publications.

Dergaa et al. (2023) further asserted that AI tools can aid scientific research in many ways; however, it is crucial to recognise that they should be used as a supplementary aid rather than a complete substitute for human creativity and ingenuity (Thorp, 2023; van Dis et al., 2023).

The use of content generated by AI in research articles can result in the incorporation of erroneous or biased material into publications, as mentioned by van Dis et al. (2023), leading to inadvertent plagiarism and concept misattribution due to lack of proper citations (Shen et al., 2023). To solve the problem of unreliability and inaccuracy, non-commercial organisations and academic collaborators have started creating large language models trained with reliable data (Poldrack et al., 2017; van Dis et al., 2023).

Therefore, it is critical for researchers to understand the tool in use in terms of its limitations so that they can maintain vigilance and integrate expert-driven fact-checking and verification processes into their work (Dergaa et al., 2023).

2.3.5 *Key Drivers of AI Tools Utilisation*

Various factors influence the use of AI tools in sectors and among university students embarking on research activities, in addition to the benefits and challenges. The research question posed by this study is as follows: What are the critical drivers of university students' use of AI-powered tools? This question explores the factors influencing university students' use of AI tools in research. By examining these factors, insights can be gained into the determinants that shape the adoption of AI tools in students' academic pursuits.

Various authors agree on the factors that influence technology adoption. The UTAUT model by Venkatesh et al. (2011) highlights the antecedent factors, such as performance expectancy, social influence, effort expectancy, and facilitation conditions, influencing the intention to use technology. Humble and Mozelius (2022) support this view and confirm that these factors directly affect consumers' intention to use banking technology. Humble and Mozelius (2022) further emphasise the

significance of social influence in user adoption studies, particularly regarding cell phones or Internet commerce. (Kim & Kim, 2022) suggested that psychological factors play a significant role in the desire to use Internet of Things (IoT) services. Furthermore, the perceived usefulness and ease of use as suggested by TAM tend to be a driver for utilisation of technology (Davis, 1989).

Talukder et al. (2020) argued that effort expectancy and facilitation conditions do not impact the behaviour intention to adopt wearable healthcare technology. This contradicts the findings Humble and Mozelius (2022) and Holzmann et al. (2020) who supported the idea that this factor influences technology adoption.

In general, while there is agreement on certain factors that influence technology adoption, such as performance expectancy, social influence, and psychological factors, there are contradictory findings on the impact of effort expectancy, facilitation conditions, and anxiety. More research is needed to better understand the complex dynamics of technology adoption and the role of these factors in different contexts.

Several studies have highlighted the importance of trust in accepting and adopting AI-powered tools for academic research (Venkatesh, 2022). When students trust technology, they have confidence that the tools will help analyse large datasets, automate research processes, and improve overall efficiency and accuracy (Chang et al., 2022). Trust in the capabilities of AI encourages students to embrace these tools as reliable and valuable resources for their research needs. Similarly, a study focusing on accepting an AI-based iris scanning tool found that trust, as per Rodríguez Cardona et al. (2021), outweighed perceived usefulness as the strongest predictor of students' behavioural intentions to adopt AI-powered tools for academic research.

Self-efficacy, an individual's belief in their ability to achieve specific goals or tasks, plays a significant role in adopting AI-powered tools for academic research (Mhlanga & Beneke, 2021). When students have a strong sense of self-efficacy, they are more confident in their ability to understand and master the complexities of AI-powered tools, leading to increased motivation and a higher likelihood of adoption. On the

contrary, students with low self-efficacy may hesitate or be reluctant to adopt AI-powered tools, doubting their ability to navigate and utilise them effectively (Ostheimer et al., 2021).

The literature highlights the significant role of trust, perceived usefulness, and self-efficacy in students' adoption of AI-powered tools. Trust in technology and its capabilities is crucial in encouraging students to embrace AI tools as reliable and valuable resources. The perceived usefulness of AI, such as improved efficiency and enhanced accuracy in data analysis, motivates students to adopt these tools (Kuleto et al., 2021). However, self-efficacy can facilitate or hinder the adoption process. Individual self-efficacy is essential in promoting the widespread adoption of AI tools (Mhlanga, 2023). Understanding these factors can inform strategies to promote the successful adoption of AI-powered tools in educational settings.

The factors influencing university students' use of AI tools are diverse and multifaceted. It is evident that technology adoption factors, such as performance expectancy, social influence, and psychological factors, influence the student's decision-making process and overall experience with AI tools. Moreover, specific AI-related factors, such as ease of use, influence the adoption of AI tools. Trust in technology emerges as a vital factor, as students need to believe that AI-powered tools will effectively enhance their academic learning. In addition, self-efficacy plays a vital role in adoption.

2.4 Conceptual Framework

The study aimed to understand the critical drivers of university students’ use of AI-powered tools. The TAM served as the theoretical foundation for this research study. The model was extended with social influence from UTAUT, information effectiveness, prior knowledge, and awareness to provide a framework to analyse the factors that lead to positive attitudes towards AI tools and adoption.

The conceptual framework depicted in the following diagram illustrates the key drivers that were explored in this study.

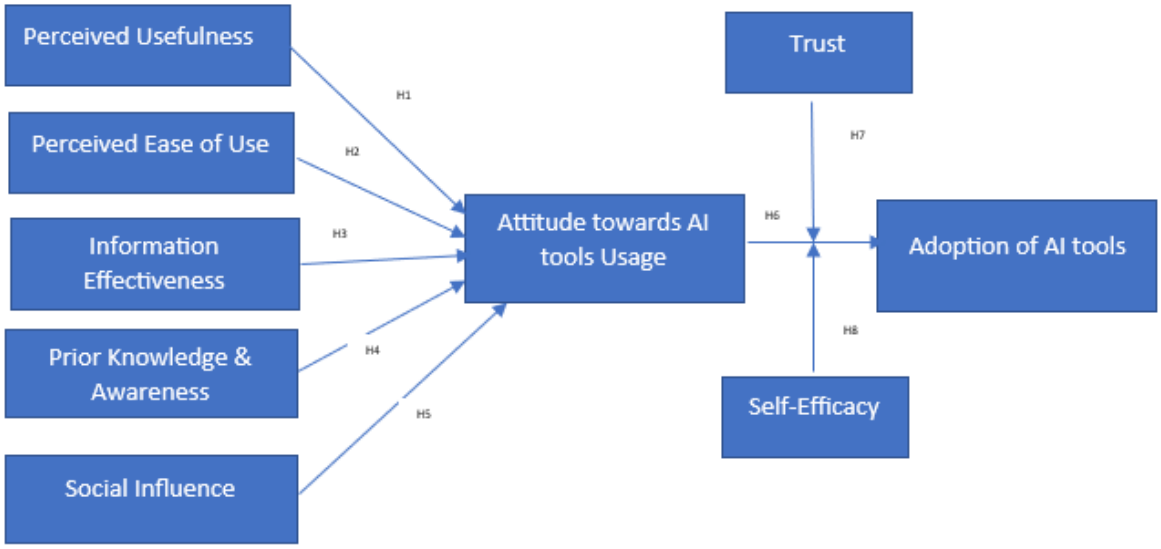


Figure 2.1 Conceptual Framework

The conceptual framework helped study the relationships between the hypothesised determinants of positive attitudes: perceived usefulness, perceived ease of use, information effectiveness, prior knowledge and awareness, and social influence. The study further tested whether the attitude toward adoption is moderated by trust and self-efficacy.

2.5 Hypotheses Development

To answer the research questions, the findings of previous studies led to the following hypotheses derived from the constructs of TAM to determine the factors driving the use of AI-powered tools by university students in South Africa.

2.5.1 *Perceived usefulness and ease of use of AI tools*

Perceived usefulness is the extent to which a person feels that adopting a system will help them enhance their performance (Davis, 1989). It is a vital motivation to use a tool. Perceived usefulness is the primary driver for mobile technology adoption, and in education, teachers consider adopting AI platforms in their lessons crucial (Al-

Rahmi et al., 2020; Oyetade et al., 2020). Sitthipon et al. (2022) affirmed that behavioural intention to adopt technology is influenced by perceived usefulness and attitude towards usage. This suggests that when students find a benefit in utilising the technology, their attitude and behaviour towards utilisation will be positively impacted, thus leading to adoption (Al Shamsi et al., 2022; Elfeky & Elbyaly, 2023; Liu et al., 2023). Therefore, as was confirmed in the study by Al Shamsi et al. (2022), there is a significant positive correlation between perceived usefulness and the intention to use voice assistants.

Perceived ease of use (PE) refers to the extent to which an individual believes that utilising a particular system would be straightforward (Başaran & Hussein, 2023; Pal & Vanijja, 2020). This involves cognitive effort and interaction to facilitate easy learning (Teo & Noyes, 2011).

In a study done by Sun and Gao (2020), it was found that perceived ease of use influenced students' intention to use the Internet. Other findings by Teo et al. (2019) and Kashive et al. (2021) found that perceived ease of use positively affects students' attitudes towards using the AI-powered e-learning platform.

On the contrary, Tahar et al. (2020) found that achieving maximum benefit from using technology and understanding its perceived usefulness continues to present challenges. Morley et al. (2020) further asserted that the use of technology may disadvantage specific populations, as factors such as socioeconomic status and institutional resources significantly influence students' technology usage.

Zhai et al. (2021) argued that AI techniques can inadvertently enable students to avoid the cognitive processing required by traditional educational practices. The emphasis was made on the risk of AI tools providing ready-made solutions, such as AI translators offering predefined words and images, which may hinder students' engagement and independent knowledge processing.

Regarding the incorporation of AI in language learning, researchers have identified its potential usefulness in providing personalised instruction and individualised learning experiences (Butt et al., 2021). Additionally, Butt et al. (2021), in the study

of the implementation of AI-powered story bots in language classrooms, found that students perceived bots as helpful for achieving their second language goals, suggesting the positive impact of AI on language learning.

Although several studies have highlighted the potential benefits of AI in education, as suggested by Kuleto et al. (2021), particularly in enhancing personal learning experiences and language learning, further investigation is needed on how AI can be effectively integrated into course content. Balancing the advantages of AI with the promotion of active learning and independent thinking remains a crucial consideration in leveraging AI's full potential for educational purposes (Luckin & Cukurova, 2019).

This led to these hypotheses.

2.5.2 *Hypothesis 1*

H1: The perceived usefulness of AI-powered tools significantly determines the attitude towards use.

2.5.3 *Hypothesis 2*

H2: Students' perceived ease of use of AI-powered tools significantly determines their attitude towards usage.

2.5.4 *Perceived Effectiveness of information from technology & AI tools*

The perception of university students regarding the effectiveness of information generated by AI tools on a particular topic is crucial to determine whether this drives utilisation. Technology is believed to be effective if the information derived from it is helpful and valuable (Huprich, 2016). The perceived effectiveness of information generated by AI tools denotes a condition by which students think that the information provided by AI tools is reliably factual and represents the truth about the world systems (Kim & Kim, 2022).

With the advancement of AI techniques, researchers have explored the potential of technology to enhance various aspects of learning and education. Kashive et al. (2021) examined how users perceive the effectiveness of AI in improving personal learning profiles (PLP), personal learning networks (PLN), and personal learning environments (PLE) in the e-learning environment. It was found that the effectiveness of AI in e-learning does not positively influence the learner's attitude towards using the technology (Kashive et al., 2021).

In another study by Sumakul et al. (2022) on students' perceptions of using AI in a writing class. Although students perceive the AI application as helpful and easy to use, participants reported some shortcomings in the sentences produced by AI. Therefore, the information is ineffective and inefficient (Chan & Lee, 2023). However, these shortcomings enabled students to generate ideas and apply critical thinking skills in their writing (Sumakul et al., 2022).

Students' perceptions of the effectiveness of the information generated by AI tools are essential in understanding the degree of adoption and use of AI tools. These perceptions also determine the degree to which a person feels they need to use a specific AI tool (Pal & Vanijja, 2020). Chan and Lee (2023) observed that students rely on information generated by AI tools due to the perception that the information is adequate.

Students tend to perceive information generated by AI tools as effective, although in some cases, there are drawbacks. Therefore, this study explored whether the effectiveness of AI-generated information is a driver of use from the South African perspective. This led to this hypothesis:

2.5.5 *Hypothesis 3*

H3: Perceived effectiveness of information generated by AI-powered tools significantly determines attitude towards usage.

2.5.6 *Students' prior knowledge and awareness of AI tools*

University students come from different backgrounds, economically, socially, and geographically. These backgrounds can determine students' prior knowledge and awareness of AI tools (Long & Magerko, 2020). Prior knowledge and awareness are regarded as the information, exposure, and understanding of specific AI tools before the students use them to enhance their learning in a university environment (Mogaji & Nguyen, 2022). In examining the impact of prior knowledge on student proficiency, the study delves into how familiarity and understanding of AI technologies shape students' competence and engagement in their use.

Students' prior knowledge and awareness influence their ability to use AI tools. García-Peñalvo (2023) suggested that gaining insight into the degree of knowledge and awareness among university students of technology is vital to effectively use technology in academics. Jalil et al. (2023) suggested that students' prior knowledge of technology for using technology, including comprehension of technology concepts, awareness of the benefits and limitations of technology, and their ability to use the tools all affect students' ability to use technology. Al-Rahmi et al. (2020) mentioned that disparities between students concerning internet access, outdated technology, and financial resources can result in differing levels of knowledge and awareness among students.

Effective use of AI tools is mainly realised among students with prior knowledge of the tools and awareness of their existence and applications (García-Peñalvo, 2023). Kashive et al. (2021) suggested that in e-learning, students who do not complete a specific module are due to being nervous about its value since they lack knowledge about it. The empirical study by Tlili et al. (2023) on using ChatGPT and user experiences found that awareness of the tool is essential in helping practical usage. Susnjak (2022) affirmed the findings, noting that if individuals can use AI tools, they can accomplish more tasks efficiently and make optimal use of them. (Essel et al., 2022) suggested that when students are familiar with AI technology and engage with it in the classroom, they can adopt the tools and their academic performance is positively impacted. On the other hand, Chang et al. (2022) argued that AI-powered

tools aim to provide specific students with timely knowledge to help them overcome challenges that develop throughout the learning process.

In conclusion, using AI tools in education can potentially transform the learning experience and support students from diverse backgrounds (Chiu et al., 2023). While some studies highlight concerns about the integrity of AI tools in education and the need for prior knowledge in using AI tools, others emphasise the positive impact of engagement with such technologies on academic performance (Perkins, 2023).

Existing studies have shown that student's prior knowledge and awareness of AI tools play a pivotal role in determining the effectiveness and efficiency of using the tools. Students with extensive technological expertise and familiarity with AI are more inclined to employ AI tools in their learning processes. This influences adoption as the tools facilitate easy access to information and enhance the performance of tasks related to their learning (Ahmad et al., 2021).

2.5.7 *Hypothesis 4*

The impact of prior knowledge and awareness on information system utilisation is crucial in determining the extent of an individual's engagement with the technology (García-Peñalvo, 2023). This led to this hypothesis:

H4: Prior knowledge and awareness of AI-powered tools significantly determine attitude towards usage.

2.5.8 *Social influence as a factor in adopting AI tools.*

Social influence is the extent to which a person believes that important people feel he or she should utilise the new system (Venkatesh et al., 2003). Attitude towards the usage of technology is affected by social influence. Abbad (2021), Andrews et al. (2021), and Alshammari (2021) found that social influence did not significantly affect students' behavioural intentions to use technology such as Moodle and virtual classrooms. On the contrary, Alasmari and Zhang (2019) and Alhwaiti (2023) found

that social influence and other UTAUT factors were significant predictors of students' behaviour intention towards using technology. This is affirmed by Ragheb et al. (2022), who found that performance expectancy, effort expectancy, and social influence significantly impact student behaviour intention to accept the application of AI chatbots among higher education students in Egypt.

For this study, the hypothesis is as follows:

2.5.9 *Hypothesis 5*

H5: Social influence significantly determines the attitude towards using AI tools.

2.5.10 *Attitude towards AI usage leads to actual adoption*

The concept of "attitude toward AI usage" refers to an individual's feelings about continuing to use the technology, considering various factors that influence their technology usage (Kemp et al., 2019; Oyetade et al., 2020). Henderson et al. (2017) found that students' attitude of students towards the use of any technology is positively influenced by its efficiency and flexibility. Furthermore, students tend to have a positive attitude towards familiar technologies if they assist them with their objectives and responsibilities (Naveh & Shelef, 2021).

Alomari and Jabr (2020) explored the link between attitudes toward AI usage and adoption in studying the effect of using AI-based educational software. The study found that positive attitudes towards AI use are associated with more significant benefits realised from using educational software, which enhanced learning outcomes and academic performance. Lee et al. (2022) found that attitude, in the context of students' adoption of AI-powered tools, refers to the emotional and psychological state characterised by feelings of worry, apprehension, and unease. These can influence students' attitudes and behaviours towards incorporating AI-based tools into their academic endeavours.

2.5.11 *Hypothesis 6*

Therefore, the attitude towards using AI tools can be influenced by various determinants, which can result in adopting the tool. In this study, the five (5) determinants were tested which influence the attitude to use a tool, hence this hypothesis:

H6: Students' attitude towards using AI-powered tools significantly determines adoption.

2.5.12 *Trust as a moderator of adoption*

Trust in AI tools has emerged as a crucial factor influencing university students' acceptance and adoption of these tools for academic research. To what extent do students trust that technology affects their belief in the effectiveness of AI-powered tools in enhancing their research efforts? Trust is essential in encouraging students to embrace AI tools as reliable and valuable resources for their research needs.

Trust was identified as a vital factor in accepting and adopting AI-powered tools (Chang et al., 2022). Trust in technology is crucial for students to believe that using AI-powered tools will effectively enhance their academic research endeavours (Chang et al., 2022). Choi et al. (2022) found that when students trust technology, they have confidence that it will help them achieve their academic goals. Trust in the capabilities of the technology encourages students to embrace AI-powered tools as reliable and valuable resources for their research needs (Choi et al., 2022).

In a study that examined the acceptance of an AI-based iris scanning tool, trust was found to be the strongest predictor of student behaviour intentions, outweighing the impact of perceived usefulness (Kelly et al., 2023). This emphasises the critical role trust in AI and technology plays in driving the adoption of AI-powered tools. The research study on technology acceptance by Weerasinghe and Hindagolla (2018) highlighted the significance of trust as a determinant of individuals' intention to use technology. Trust in the system and trust in the information provided by technology,

including AI tools, positively influence users' acceptance and adoption of these tools Wang et al. (2020).

In conclusion, trust in AI tools is a vital factor that significantly influences university students' adoption of the tools. Students' trust in the technology plays a crucial role in their belief that AI-powered tools can effectively enhance their research endeavours. Studies have shown that higher levels of trust in AI tools lead to improved learning performance, increased student engagement, and increased intention to use the tools (Wang et al., 2021). Therefore, establishing trust in AI-powered educational tools is essential to maximise their potential benefits for students' academic success. Trust is a crucial factor influencing university students' adoption of AI-powered tools. It is a subjective attitude that enables individuals to make valuable decisions regarding technology usage (Chang et al., 2022).

2.5.13 *Hypothesis 7*

This study tested trust as a moderating factor for the relationship between the attitude toward the use and the adoption of AI-powered tools. Hence,

H7: Trust in AI tools moderates the relationship between attitude towards AI usage and actual adoption.

2.5.14 *Self-efficacy as a moderator of adoption*

Self-efficacy refers to an individual's belief in their ability to achieve specific goals or tasks (Mhlanga, 2023). It is a psychological concept that significantly impacts motivation and influences how individuals approach different activities (Theobald, 2021). In adopting AI-powered tools for academic research, self-efficacy plays a crucial role in determining students' willingness to use these tools effectively. Students with high levels of self-efficacy about AI-powered tools are more likely to perceive themselves as competent and capable of using them to improve their research endeavours (Ostheimer et al., 2021). In contrast, students with low self-efficacy may hesitate or be reluctant to adopt AI-powered tools. They may doubt their

ability to navigate and utilise these tools effectively, leading to a lack of confidence in their skills and a potential aversion to incorporating such tools into their research practices (Ostheimer et al., 2021).

Mirchi et al. (2020) studied the impact of self-efficacy on academic performance in a blended learning environment using intelligent tutoring systems study. The relationship between students' self-efficacy and academic performance in a blended learning environment using intelligent tutoring systems was explored. The results indicated that students with higher levels of self-efficacy performed better academically using the AI-based tutoring system than those with lower self-efficacy. Another study by Kizilcec et al. (2017) investigated the relationship between self-efficacy and academic performance in online learning environments. The researchers found that students with higher self-efficacy in using AI tools and online platforms performed better academically than those with lower self-efficacy. Additionally, the study highlighted the importance of designing interventions to improve student self-efficacy and academic outcomes.

Students with higher self-efficacy regarding AI-powered tools are more likely to perceive themselves as competent and capable, leading to a greater willingness to utilise them effectively (Lee et al., 2022). Conversely, Yilmaz and Yilmaz (2023) argued that students with lower self-efficacy may hesitate or resist adopting such tools due to doubts about their ability to navigate and use them. To promote adoption, educators and institutions must provide training, resources and support tailored to enhance students' self-perception of competence (Yilmaz & Yilmaz, 2023). By nurturing higher levels of self-efficacy, students can become more confident and proficient in using AI-powered tools, ultimately benefiting their academic pursuits and success (Kelly et al., 2023).

In conclusion, self-efficacy is critical in adopting AI-powered tools for academic research. Students with higher self-efficacy regarding these tools are more likely to perceive themselves as competent, leading to increased motivation and improved academic performance.

2.5.15 *Hypothesis 8*

This study researched self-efficacy as a moderating factor in the relationship between attitude and actual adoption.

H8: The student's self-efficacy moderates the relationship between attitude towards AI usage and actual adoption.

2.6 Conclusion

The study aimed to quantitatively understand the key drivers of using AI-powered tools by students when conducting academic research. Reviewing the theoretical and empirical literature in the field. The chapter provided a comprehensive overview of the theoretical foundations and critical constructs relevant to the study. It also examined previous studies that used various theories to understand the AI phenomenon in education and research. The chapter set the stage for empirical investigation and analysis, contributing to a deeper understanding of the drivers of using AI tools in academic research activities.

CHAPTER 3. RESEARCH METHODOLOGY

3.1 Introduction

This chapter outlines the methodological approaches adopted in this study to understand the drivers of using AI-powered tools in academic research in South African universities. It explains the data collection, analysis, presentation, and interpretation methods. The methodological approaches are presented in line with the research objective, specific objectives, research questions, and the conceptual framework introduced in earlier chapters. Essential concepts discussed in this chapter include the research philosophy, approach, design, strategy, techniques, and procedures. These are examined in the context of their reliability and validity within the study.

3.2 Research philosophy

According to Coates (2021), the philosophical presumptions researchers make when conducting a study are the first step in the research design process. The conduct and writing of the study are influenced by the world views, paradigms, and beliefs that the researchers bring to the research undertaking. Goertz and Mahoney (2012) suggest that the interplay between ontological and epistemological assumptions, meta-theoretical underpinnings, research questions, and research techniques become prominent in determining one's philosophical perspective as a researcher.

This study adopted the positivist research philosophy as the inquiry paradigm. It is based on quantitative observations that can be statistically analysed and is linked to scientific hypotheses Park et al. (2020). Its ontological, atomistic perspective of the world comprises distinct, observable occurrences and elements that interact in a predictable, observable way (Coates, 2021). According to positivists, the success of natural science results from scientists' reluctance to stray from what is corroborated by empirical data, especially data gathered through close observation of occurrences.

Following the positivist philosophy, this study identified hypotheses, which were tested through analysis of quantitative observations gathered from a questionnaire survey distributed among university students to understand the drivers of AI-powered tools used in academic research in a South African institution. The adopted research processes, including data collection and analysis, were designed per the positivist research paradigm.

3.3 Research Approach

The study adopted the survey research approach, which involves collecting data from a sample of individuals using standardised questionnaires or interviews (Saunders et al., 2009). This method allows researchers to gather information on a population's attitudes, opinions, behaviours, or characteristics (Saunders et al., 2009). Surveys can be conducted through various modes, including face-to-face interviews, telephone interviews, mailed questionnaires, online surveys, or a combination of these methods. In this study, a standardised questionnaire was distributed online among university students at Witwatersrand University in South Africa. It was designed to gather their experiences and opinions regarding university students' use of AI-powered tools in academic research. Using this approach, the study started with the sampling of the participants, where a sample of university students from the University of Witwatersrand was selected to represent a larger population.

The sampling was followed by the design of a questionnaire comprising a set of closed-ended and some open-ended questions focused on understanding the use and opinions of students about tools powered by AI. The questionnaire was then distributed among the sampled population by online means. After data collection, the study analysed the responses to identify patterns, trends, and relationships in line with the set hypotheses.

3.4 Research Strategy

In this study, the nonexperimental, correlational quantitative research design was adopted as the strategy for inquiry. According to Lewis et al. (2003), quick and once-off data collection from natural settings is best served by correlational research. This aids in the external validity of generalising findings to actual scenarios. To achieve this, a questionnaire survey was administered among students from Witwatersrand University. The survey comprised two sections, the first one being demographics and the second part being a standard set list of questions with a five-point Likert scale defined online on Qualtrics (Saunders et al., 2009). This allowed statistical analysis and precise measurement of the relationships between variables. (1) the relationship between perceived usefulness and adoption of AI tools; (2) the relationship between ease of use and adoption of AI tools; (3) the relationship between prior knowledge or awareness and use of AI tools; and finally (4) the relationship between perceptions of AI-generated information and the use of AI tools. Qualtrics did not collect personal information from participants. In addition, the participant information sheet disclosed that no personal information was collected, and participants had to consent before accessing the study.

3.5 Research Method

The study adopted the quantitative research method to examine the key drivers of university students' use of AI-powered tools. The method involved using a research survey approach to collect and analyse numerical data to test hypotheses, identify patterns, or quantify relationships between variables. This method relies on statistical techniques to analyse the data and draw conclusions. According to the postulation of (Al Shamsi et al., 2022), the approach allowed the researcher to statistically understand reality, make inferences and generalise about a large student population's use of AI tools. The approach also allowed statistical analysis of the relationships between independent and dependent variables (Saunders et al., 2009).

3.6 Research Time Horizon

The research study followed the cross-sectional time horizon. According to Saunders et al. (2009), data is collected simultaneously in cross-sectional studies. Setia (2016) argues that a cross-sectional study uses several individuals simultaneously, and the variables are observed without influencing them. Consistent with this, the study collected data from several Witwatersrand University students once-off during the last semester of the 2023 academic year.

3.7 Research Techniques and Procedure

3.7.1 *Data Collection*

Following the convenience sampling design, data was collected using a questionnaire survey (Saunders et al., 2009). The survey instrument was conveniently emailed to undergraduate final year and postgraduate (honours, masters, and doctorate) students from Wits University.

3.7.2 *Population*

The targeted population studied are the undergraduate final year and postgraduate (honours, masters, and doctorate) students from Wits University. This population was selected based on the likelihood of their exposure to research projects and their alignment with the criteria established for this study. The survey was circulated to 14 775 students.

3.7.3 *Sample and Sampling Method*

The sample size for this study was 271 participants (n=271), of which 21 responses were omitted due to having more than 10% missing data. The targeted sample was n=400, as a rounded off figure of n = 375 computed from a population of 14 775 with a margin of error of 5% and confidence level of 95% (Saunders et al., 2009). This sample size was an estimate based on the unknown number of students that utilise AI tools. Therefore, the sampling method that was adopted was the convenience

sampling framework (Saunders et al., 2009). According to Nikolopoulou et al. (2020), convenience sampling is a nonprobability sampling technique in which the units chosen for the sample are the ones the researcher can access quickly. In this study, the response rate of n=271 that was achieved could have been caused by targeted respondents not being willing to participate in the study, and probably the survey fatigue due to the high number of surveys that were published by various research students, hence the convenient sampling approach was adopted due to availability of students that are willing to participate and the number of AI tool users being unknown.

3.7.4 *Procedure for data collection*

The survey was defined in Qualtrics with mandatory and non-mandatory questions set. The validity period for the online survey was first set at one week for the pilot study. The pilot study was conducted with 10 participants who provided feedback on the grammar and layout concerns of the research questions.

Subsequently, the survey link was distributed to the target population by email. Responses were recorded in Qualtrics throughout the validity period of the survey. After the validity period, all responses were exported to Excel and uploaded to SPSS to check missing data, outliers, or errors, and finally, statistical analysis to gather inferences on variables in the study. The collected data and results will be stored for five (5) years and discarded afterwards.

3.7.5 *Data Collection Instrument*

The questionnaire comprised Sections A and B. Section A consisted of demographics-related questions such as gender, age, level of study, an indication of whether a participant is conducting a research study, and lastly, the AI tools used in their research tasks. Section B comprised questions related to perceptions on the usefulness, ease of use, effectiveness of AI generated information, prior knowledge and awareness, attitude towards AI tools, actual adoption of AI tools, self-efficacy, trust, and social influence. The research questions were adapted from previous

sources, and others were developed for the purpose of this study based on what was mentioned by other authors.

Each hypothesis was tested with five questions. A participant selected a suitable answer based on the 5-point Likert scale, where 1 indicates strong disagreement and 5 indicates strong agreement.

Table 3.1: Key variables in the research instrument

Construct	**Measurement**	**Reference**
Perceived usefulness	1. I think using AI tools can improve my productivity. 2. I think using AI tools can improve my performance. 3. using AI tools can encourage me to finish my tasks quickly. 4. I think using AI tools positively impacts my learning outcomes. 5. I think using AI tools can help me to complete my tasks.	(Li, 2023) (Al Shamsi et al., 2022)
Perceived ease of use	6. Learning how to use AI tools is accessible to me. 7. My interaction with AI tools is clear and understandable. 8. I find AI tools to be easy to use. 9. I find the user interface of the AI tools easy to navigate. 10. Using AI tools feels effortless and intuitive.	(Li, 2023) (Al Shamsi et al., 2022)
Perceived effectiveness of information	11. I find information generated by AI tools accurate. 12. I find information generated by AI tools reliable. 13. I find that information generated by AI tools is from trustworthy sources. 14. AI tools generate all the necessary information I need. 15. I find the information generated by AI tools relevant to my needs	Self developed

Construct	Measurement	Reference
Prior knowledge and awareness	16. Having prior knowledge and awareness of AI tools helps me use the tools efficiently. 17. Having experience with similar AI tools helps me use the tools efficiently. 18. Being an expert in using AI tools helps me to use the tools efficiently. 19. Being trained in using AI tools helps me know how to use them efficiently. 20. Being familiar with concepts related to AI tools helps me know how to use AI tools efficiently.	Self developed
Attitude towards AI tools usage	21. I intend to use AI tools in the future. 22. I will recommend using AI tools to my friends and family. 23. I will keep myself updated with the latest AI tools. 24. I believe using AI tools can improve my results. 25. I am open to exploring new AI tools.	(Li, 2023) (Alharbi & Drew, 2014)
Actual Adoption	26. I adopt AI tools in academic research tasks. 27. I adopt AI tools to improve my final academic results. 28. I adopt AI tools to improve the quality of my assignments and projects. 29. I adopt AI tools to positively affect my ability to manage my time effectively. 30. I adopt AI tools to positively impact my overall academic confidence.	(Li, 2023) (Alharbi & Drew, 2014)
Trust	31. I trust AI tools to protect my personal information and maintain my privacy. 32. I trust AI tools to consistently deliver reliable outcomes. 33. I trust AI tools to provide accurate results or information. 34. I trust AI tools to be transparent in how they operate. 35. I trust AI tools to make fair and unbiased decisions.	(Choi et al., 2022)

Construct	Measurement	Reference
Self-Efficacy	36. I have confidence in my ability to use AI tools effectively. 37. Knowing how to use AI tools affects my attitude towards usage and adoption. 38. I have confidence in learning new AI tools. 39. I can quickly grasp and utilise new features or functionalities of AI tools. 40. I can achieve the desired outcomes or results through using AI tools.	Self developed
Social Influence	41. People who are important to me think I should use AI tools. 42. People who influence my behaviour think I should use AI tools. 43. The seniors in my university are helpful in using AI tools. 44. In general, the university has supported using AI tools. 45. People I respect think I should use AI tools.	(Abbad, 2021) (Andrews et al., 2021)

3.8 Quality Assurance

In this study, ensuring the research instrument's internal and external validity and reliability was essential. The importance of validity and reliability can best be demonstrated by the statement by Kennedy et al. (2019) that a causal relationship should exist between the questionnaire, its component questions or statements, and the findings extracted using statistical data analysis.

3.8.1 *External Validity*

To ensure that there was diversity in the participants, demographic data such as gender, age, and level of study were collected for external validity (Saunders et al., 2009). These variables were assessed to understand how these characteristics impact behaviour.

3.8.2 *Internal validity*

The validity of the questionnaire was ensured by conducting a pilot study by distributing the survey to ten participants who provided feedback on the content to ensure that the survey aligned with its intended measurement (Rahman et al., 2022). Participants' feedback helped to determine whether the survey adequately covered the relevant factors to fulfil its intended purpose (Abdullah et al., 2022). Murillo-Llorente et al. (2022) mentioned that face validity concerns the extent to which a test measures the variables it intends to assess. In this study, the research instrument covered all the variables under study.

Furthermore, construct validity was tested with normality tests by calculating composite variables and averaging individual items within each construct. The Kolmogorov-Smirnov and Shapiro-Wilk tests were utilised to assess normality (Field, 2018).

3.8.3 *Reliability*

The reliability in this study involved ensuring consistency and stability in measuring variables and responses. Therefore, straightforward, unambiguous survey questions allowed participants to understand the questions without needing interpretation. The pilot study helped eliminate this risk. Furthermore, the survey was distributed standardised with consistent instructions, order of questions, and response options to minimise variability in data collection.

The Cronbach alpha coefficient (α) was used to measure internal consistency and to determine those elements on a scale or construct that measure similar underlying concepts (Field, 2018). Quality control checks were conducted throughout the data collection by monitoring data entry accuracy, reviewing completed surveys for errors, and addressing any inconsistencies or missing data. Item analysis was conducted to eliminate poorly performing or redundant survey items that could have introduced measurement errors or decreased reliability (Saunders et al., 2009).

Table 3.2 Consistency Determination

RQ#	Research Question	Hyp #	Hypothesis	Questions	Data analysis method
i.	What are the key drivers of university students' use of AI-powered tools?	H1	The perceived usefulness of AI-powered tools significantly determines attitude towards usage.	Q 1 - 5	Regression and Correlation analysis
		H2	Perceived ease of use of AI-powered tools significantly determines attitude towards usage.	Q 6 - 10	Regression and Correlation analysis
		H3	The perceived effectiveness of information generated by AI-powered tools significantly determines attitude towards usage.	Q11 - 15	Regression and Correlation analysis
		H4	Prior knowledge and awareness of AI-powered tools significantly determine attitudes towards usage.	Q16 - 20	Regression and Correlation analysis
		H5	Social influence significantly determines the attitude towards the usage of AI tools.	Q41 - 45	Regression and Correlation analysis
		H6	Students' attitude towards using AI-powered tools significantly determines adoption.	Q21 - 25	Regression and Correlation analysis
		H7	Trust in AI tools moderates the relationship between attitude towards AI usage and adoption.	Q31 - 35	Regression and Correlation analysis
		H8	The student's self-efficacy moderates the relationship between attitude towards AI usage and actual adoption.	Q36 - 40	Regression and Correlation analysis
ii.	How do students' prior knowledge and awareness impact AI tool usage?	H4	Prior knowledge and awareness of AI-powered tools significantly determine attitudes towards usage.	Q16 - 20	Regression and Correlation analysis
iii.	How do perceived usefulness and ease of use impact adopting AI-powered tools?	H1	The perceived usefulness of AI-powered tools significantly determines attitude towards usage.	Q 1 - 5	Regression and Correlation analysis
		H2	Perceived ease of use of AI-powered tools significantly determines attitude towards usage.	Q 6 - 10	Regression and Correlation analysis
iv.	To what extent do students' perceptions of AI-generated	H3	The perceived effectiveness of information generated by AI-powered tools significantly determines attitude towards usage.	Q11 - 15	Regression and Correlation analysis

	information influence their attitude towards using AI tools?				

3.8.4 *Pre-testing of the Questionnaire*

Pre-testing a questionnaire is a critical quality assurance step that helps researchers develop high-quality survey instruments and collect accurate and reliable data for their research studies (Coates, 2021). The questionnaire was pre-tested on 4 males and 6 females within the age categories of 30-39 and 40-49 from the Master of Management of Digital Business class at Wits University, to ensure that the questionnaire was clear, understandable, and relevant to the target population. Additionally, the study wanted to identify and rectify any ambiguities, biases, or errors in the questionnaire before widespread distribution, improve the validity and reliability of the questionnaire by improving its design and structure, and increase the cooperation of the respondents. Lastly, pretesting was performed to reduce survey nonresponse by minimising respondent burden and improving questionnaire flow.

To execute the pre-testing process, the study first selected a small sample of individuals who closely resembled the study's target population to ensure that the pre-test participants could provide relevant feedback on the questionnaire. Next, the questionnaire was administered to the pre-test participants using the same methods and procedures planned for the primary data collection phase. This was followed by an analysis of the feedback provided by the participants to identify any problems with the questionnaire. Common issues included ambiguous questions, response options that are difficult to understand, and questions that are perceived as irrelevant or intrusive. Based on feedback received during the pre-testing phase, necessary revisions were made to the questionnaire to address identified issues and improve its clarity, validity, and reliability. This involved rephrasing questions, modifying response options, and removing redundant and unnecessary items. After the revisions, the questionnaire was finalised and administered to the larger sample population participating in the study.

3.9 Data analysis and interpretation

Descriptive and inferential statistics were used for data analysis to examine the correlation between determinants (perceived usefulness, perceived ease of use, effectiveness of information, prior knowledge and awareness, social influence) and the attitude toward the usage of AI tools usage; test the moderating variables (trust and self-efficacy), and the adoption of AI tools when conducting research. Regression analysis was applied to identify the relationships' nature, strength, and significance and make predictions or explanations based on the collected data (Saunders et al., 2009).

Construct validity was tested using exploratory factor analysis (EFA) (Murillo-Llorente et al., 2022) to identify the underlying factors among all items on the measurement scale. Items with a factor loading of at least 0.4 falling under the same factor indicated that they measure the same construct (Field, 2018).

3.10 Ethical Considerations

The data collected was stored on a password-protected computer, which the author and the supervisor access. Data were aggregated during statistical analysis, so the possibility of associating responses with specific individuals was eliminated. Data collection only began after the Ethics Committee granted ethics clearance and formal approval was received from the University Registrar to distribute the survey link.

3.11 Conclusion

This chapter has explained the methods used to address the study's research questions. It has shown that the overall methodology is based on a positivist research philosophy, which guided the data collection and analysis procedures. The chapter has shown that the research survey was adopted as the research approach, while the research strategy used the nonexperimental, correlational quantitative research design. The data collection included sampling participants, designing, and distributing the questionnaire, and data analysis. The questionnaire was pre-tested before it was used to collect the complete dataset. The chapter has also shown that

all research processes adhered to research ethics principles and that the validity and reliability of the instruments and all processes were considered. The presented methodological approach is aligned with the research questions and hypotheses of the study.

CHAPTER 4. PRESENTATION OF RESULTS

4.1 Introduction

This study examined the key drivers of university students' use of AI-powered tools. This chapter presents results following the methodology outlined in the previous chapter. The chapter discusses sample characteristics and demographic profiles of respondents in the first section. Furthermore, the research instrument is analysed, focusing on the reliability of the measurement scale. After that, the chapter presents normality tests that help determine the types of statistical tests for the study. Descriptive statistics of the constructs are presented before conducting correlation and regression analyses to test the specified hypotheses. In the end, a summary of the chapter is presented that focuses on whether the hypotheses were supported or not.

4.2 Sample Characteristics and Demographic Information

In this study, a convenience sampling approach was employed, wherein an online questionnaire was disseminated to potential participants, and only those who voluntarily opted to partake were included. A total of 271 responses were garnered through the online survey. The study specifically targeted students affiliated with Wits University who possessed prior experience in utilising AI-powered tools within their academic research pursuits.

However, prior to commencing the analysis, a meticulous data-cleaning process was undertaken. During this phase, 21 responses were identified for exclusion from the dataset. These exclusions were predicated on the criterion of having more than ten percent missing values, following the methodology outlined by (Little, 2021). Missing values denote data points that respondents did not furnish.

After this data-cleansing procedure, the final sample comprised 250 respondents, thereby ensuring that only comprehensive and dependable data were utilised for

subsequent analyses. The ensuing figures offer descriptive statistics pertaining to the demographic variables under examination in this study.

4.2.1 *Age groups*

The sample distribution in terms of age groups is shown below:

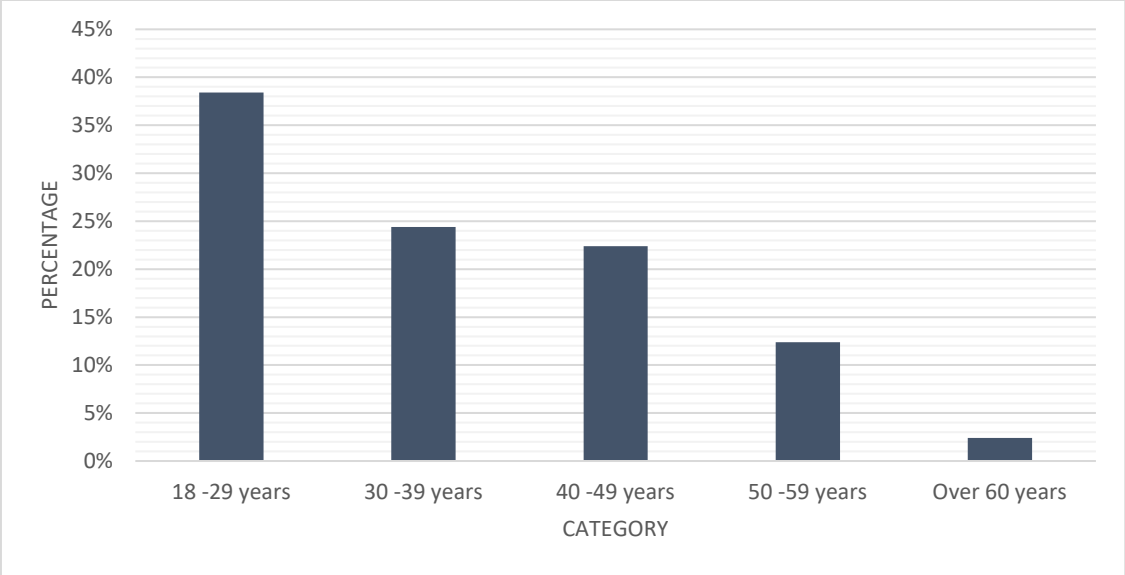


Figure 4.1 Sample population distribution by age groups

The researcher examined the age composition of our sample population, shedding light on the diversity and representativeness of participants. The data revealed the following insights:

i. 18 - 29 Years: The largest age group, comprising 38.4% of the total participants, represents the university's vibrant younger student population. These individuals actively engage in academic pursuits, contributing significantly to the study.
ii. 30 - 39 Years: The 24.4% of participants within this age range indicate a substantial presence of students in their 30s. Despite being slightly older, they remain committed to academic research, emphasising their relevance to our investigation.

iii. 40 - 49 Years: With 22.4% of the sample, this category represents students in their 40s. Their inclusion adds diversity to our respondent pool, reflecting a wide age range and enhancing the sample's representativeness.

iv. 50 - 59 Years: Comprising 12.4%, this group includes participants in their fifties. Their presence suggests more extensive academic experience and potentially different research needs compared to younger cohorts.

v. Over 60 Years: Although a small proportion (2.4%), the inclusion of older students in our sample is noteworthy. These individuals contribute valuable perspectives, bridging generational gaps and enriching our understanding.

vi. This research study benefits from a well-rounded sample that spans various age groups, providing context for our research within the university community. the Differences were observed between our findings and previously published research underscore the uniqueness of our study and highlight areas where we address existing gaps and limitations. By considering these nuances, the researcher gained deeper insights into the impact of age on academic engagement and research endeavours.

4.2.2 *Gender*

The gender distribution of the sample provides essential information about the diversity of the participants. This is summarised in Figure 4.2.

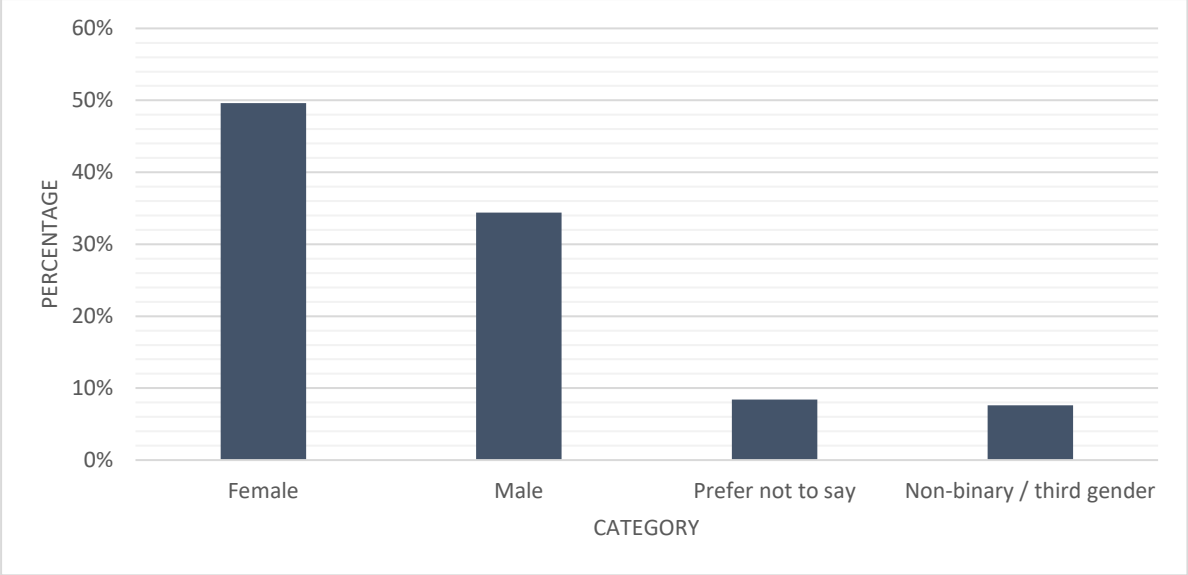


Figure 4.2 Sample population distribution by gender

The gender distribution within our sample provided valuable insights:

i. Female: Representing 49.6%, the majority of respondents identify as female. This substantial presence highlights active participation by women students in academic research.

ii. Male: Comprising 34.4%, the male category also contributes significantly. It reflects a substantial number of male students engaged in research endeavours.

iii. Inclusivity and Diversity:

"I prefer not to say" (8.4%): This category emphasizes inclusivity, recognizing individuals who choose not to disclose their gender. "Non-binary/third gender" (7.6%): Acknowledging diverse gender identities, this group ensures representation beyond the binary norm.

This research study was commitment to inclusivity and recognition of diverse perspectives enriches our findings and contributes to a comprehensive understanding of gender dynamics in academic research.

4.2.3 *Level of Study*

Respondents were asked to indicate their current level of study at Wits University. The following figure summarises the sample distribution in terms of their current level of study.

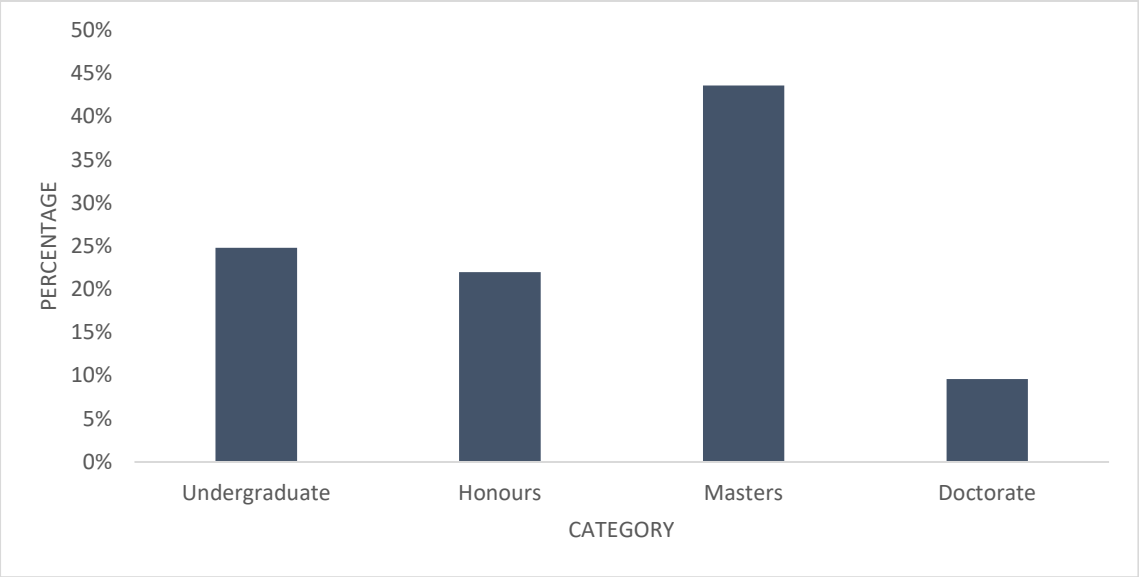


Figure 4.3 Sample population distribution by level of study

The results show that most students who participated in the study were doing Masters programmes, making up 43.6% of the sample. This significant representation of master's students implies that the study encompasses the perspectives and experiences of a diverse group of students who are in the advanced stages of their academic journey. Thus, the study includes a substantial number of respondents who have progressed to higher levels of academic study, likely engaging in more complex research projects. The undergraduate category, representing 24.8% of the sample, indicates a significant presence of students in their early stages of the academic journey. Many students (22.0%) indicated they were doing honours degrees. This also constitutes a considerable number of students involved in advanced academic research. The Doctorate category, at 9.6%, reflects a more minor but notable proportion of doctoral students in the sample. These individuals likely engage in highly advanced research and may contribute uniquely to the study.

4.2.4 *Artificial Intelligence Tools Used*

The students were asked to indicate the AI tools they have used in their academic research. Results are summarised in Table 4.1.

Table 4.1 AI Tools

Combination of AI Tools	Frequency	Percentage of Users
ChatGPT	40	16.0%
ChatGPT, Google Bard	6	2.4%
ChatGPT, Grammarly	16	6.4%
ChatGPT, Quillbot	10	4.0%
Google Bard	13	5.2%
Grammarly	20	8.0%
Litmaps	15	6.0%
Quillbot	19	7.6%
Scite	11	4.4%
Other	15	6.0%
Multiple AI Tools Combinations (2 or more tools)	23	9.2%

The data distribution in Table 4.1 reveals that ChatGPT and Grammarly are the most popular choices used by the university students in the sample. ChatGPT and Grammarly: These two tools emerge as the most popular choices, with 40 instances (16.0% of the sample) relying on ChatGPT and 20 (8.0%) utilising Grammarly. Their combined impact underscores their effectiveness in aiding academic endeavours.

Other Individual Tools:

i. Quillbot: 19 students (7.6%) benefit from Quillbot's paraphrasing capabilities.
ii. Google Bard: 13 participants (5.2%) leverage Google Bard for research tasks.
iii. Litmaps: 15 students (6.0%) find value in List maps, emphasizing its role in organising information.
iv. Scite: 11 respondents (4.4%) utilise Site, possibly for web-based research.
v. Multiple AI Tool Combinations:
vi. There were 23 students (9.2%) exhibit adaptability by using two or more tools concurrently. This versatility underscores their strategic approach to research.
vii. The research posits this diverse tool landscape reflecting the growing importance of AI in supporting academic work. As Kirk and Ferguson (2022) aptly note, these tools enhance efficiency, accuracy, and creativity across various research domains. This diverse tool usage underlines the importance of AI in supporting various aspects of academic work (Kirk & Ferguson, 2022).

The following section discusses the reliability of the measurement scales used in the study.

4.3 Reliability of the Measurement Scales

This section discusses the reliability analysis of the measurement scales that were used in this research study. The constructs under examination include perceived usefulness (PU), perceived ease of use (PEU), perceived information effectiveness (PIE), prior knowledge and awareness (PKA), attitude towards use (ATU), actual adoption (AA), trust (TR), self-efficacy (SE), and social influence (SI). As highlighted

by Teixeira et al. (2021), this statistical approach is crucial for assessing the internal consistency of the measurement scales associated with these constructs.

The methodology employed entails evaluating the Cronbach alpha value both before and after the removal of an item. This process aims to ascertain whether eliminating any item from a specific construct could potentially enhance the alpha value Hayes and Coutts (2020).This procedure ensured that all items within a construct exhibited strong correlations, signifying their consistent measurement of the same underlying construct (Amirrudin et al., 2021). The results are summarised in the following table:

Table 4.2 Summary of reliability analysis

Construct	Code	Number of items	Cronbach's alpha (before adjustment)	Items deleted	Cronbach's alpha (after adjustment)
Perceived usefulness	PU	5	0.880	None	0.870
Perceived ease of use	PEU	5	0.850	None	0.845
Perceived information effectiveness	PIE	5	0.838	None	0.832
Prior knowledge and awareness	PKA	5	0.770	None	0.750
Attitude towards use	ATU	5	0.797	None	0.784
Actual adoption	AA	5	0.858	None	0.848
Trust	TR	5	0.858	None	0.853
Self-efficacy	SE	5	0.705	None	0.704
Social influence	SI	5	0.807	None	0.790

The reliability analysis results comprehensively assess the internal consistency of the measurement scales used in this study. The Cronbach's alpha coefficients for each construct were examined before and after considering potential item deletions. A widely accepted level of a reliable measure typically corresponds to a Cronbach alpha coefficient of at least 0.7 (Field, 2018).

Perceived usefulness, perceived ease of use, perceived information effectiveness, attitude towards use, actual adoption, prior knowledge and awareness, self-efficacy, trust, and social influence constructs all exhibited high levels of internal consistency, as their initial alpha coefficients were above the 0.7 cut-off point. Notably, after evaluating potential item deletions, there were no improvements in the alpha coefficients in all cases, implying that deleting an item could not further improve the scale's reliability. Consequently, no items were deleted in all constructs.

The implications of these reliability analysis results are substantial for the subsequent sections of this study. With the constructs' reliability confirmed, each construct's composite measures can be calculated (Teixeira et al., 2021). These composite measures, which comprise combined responses of multiple elements within each construct, will serve as robust and consistent variables for further analysis.

The following section presents normality tests.

4.4 Normality Tests

The composite variables were calculated by averaging the individual items within each construct. This method involved summing up the scores of all items related to a specific construct and dividing by the total number of items. This allowed for the creation of single composite variables that represent each construct. The test for normality is a crucial step in the analysis process. It helps determine whether the data distributions approximate a normal distribution, an underlying assumption of many statistical tests (Gupta, 2021). The normality test ensures that the data are suitable for the chosen statistical analyses and provides valuable information on the distribution characteristics of the variables (Field, 2018). To assess normality, both

the Kolmogorov-Smirnov and Shapiro-Wilk tests were employed. The results of these tests are presented in the table below, which sheds light on the distribution characteristics of the data sets.

Assessing the normality of the data is imperative for ensuring the robustness and validity of subsequent statistical analyses. Deviations from normality can impact the accuracy and reliability of statistical tests, potentially leading to erroneous conclusions (Field, 2018). Therefore, by conducting thorough normality tests, researchers can ascertain the appropriateness of employing parametric statistical methods and make informed decisions regarding data analysis techniques. Additionally, understanding the distribution characteristics of the variables allows researchers to employ suitable data transformation techniques or alternative statistical approaches if the data deviate significantly from normality. Overall, the normality assessment serves as a critical step in the analytical process, guiding researchers in the selection of appropriate statistical methods and ensuring the integrity of the study findings.

Table 4.3 Tests for normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	Df	Sig.	Statistic	Df	Sig.
PU	.164	250	.000	.883	250	.000
PEU	.158	250	.000	.927	250	.000
PIE	.115	250	.000	.968	250	.000
PKA	.125	250	.000	.958	250	.000
ATU	.123	250	.000	.953	250	.000
AA	.128	250	.000	.949	250	.000
TR	.105	250	.000	.969	250	.000
SE	.133	250	.000	.966	250	.000
SI	.103	250	.000	.979	250	.001

a. Lilliefors Significance Correction

The results of the normality tests, employing both the Kolmogorov-Smirnov and Shapiro-Wilk tests, are reported in Table 4.3 above. For all constructs, the p-values associated with both normality tests are highly significant ($p < 0.001$), indicating that the data deviate significantly from a normal distribution. In other words, the standard distribution assumption does not hold for any of the constructs in the study.

The implications of non-normally distributed data are noteworthy. First, it implies that parametric statistical tests, which assume normality, are appropriate for analysing these data sets (Field, 2018). Violating the normality assumption can lead to biased results and affect the validity of statistical inferences (Gupta, 2021). Nonparametric tests designed for nonnormally distributed data are more suitable in such cases. According to Gupta (2021), these tests do not rely on the assumption of a normal distribution and can provide robust analysis even when the data are not normally distributed. Therefore, this study used nonparametric tests for further analysis.

4.5 Descriptive Statistics

In this section, the focus is on descriptive statistics for composite constructs. It is important to note that the data in this study were collected using a 5-point Likert scale, with one indicating "strongly disagree" and five representing "strongly agree." The mean score serves as a measure of central tendency and offers insights into the collective perception of the constructs. According to the 5-point Likert scale, a mean above 3.5 implies that, on average, respondents leaned toward agreement with the items, indicating a positive perception of the constructs being measured (Field, 2018). Conversely, Field (2018) states that a mean score below 3.5 suggests a more neutral or negative perception, with average respondents leaning towards disagreement or neutrality.

In addition, the standard deviation (SD) measures the dispersion or spread of data points around the mean. A higher SD suggests more significant response variability, with data points scattered widely from the mean (Gupta, 2021). On the contrary, a

lower SD indicates that the responses are tightly clustered around the mean, signifying lower variability (Field, 2018).

Skewness measures the asymmetry of the probability distribution of a real-valued random variable about its mean (Gupta, 2021). It indicates whether the data are skewed to the left (negatively skewed) or the right (positively skewed) about the mean.

Kurtosis measures the peakedness or the degree to which a probability distribution departs from normality. It indicates whether the distribution is peaked (leptokurtic) or flat (platykurtic) compared to a normal distribution (Mishra et al., 2019). Positive kurtosis indicates a distribution with heavier tails and a more pronounced peak. Negative kurtosis suggests a distribution with lighter tails and a flatter peak than a normal distribution (Field, 2018). A zero kurtosis value means the distribution has the same kurtosis as a standard normal distribution (Field, 2018).

The following table is a summary of these descriptive statistics:

Table 4.4 Descriptive statistics

	N	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
PU	250		.828	-1.312	.154	2.548	.307
PEU	250	3.932	.750	-.984	.154	1.521	.307
PIE	250	3.407	.772	-.563	.154	.333	.307
PKA	250	3.753	.700	-.659	.154	1.146	.307
ATU	250	3.994	.693	-.534	.154	.063	.307
AA	250	3.757	.820	-.710	.154	.586	.307

TR	250	3.344	.876	-.442	.154	-.376	.307
SE	250	3.883	.597	-.357	.154	.006	.307
SI	250	3.331	.825	-.303	.154	-.304	.307

The descriptive statistics in the table describe the characteristics of the composite constructs under study, each representing an essential facet in analysing the drivers of using AI tools in academic research. Descriptive statistics per each construct are discussed in the following sections:

4.5.1 *Perceived Usefulness (PU)*

The mean score for PU is 3.949, indicating that, on average, respondents agreed with the perceived usefulness of AI-powered tools for their academic research. This aligns with the construct's focus on assessing how students perceive these tools' practical benefits and advantages. The standard deviation (SD) of 0.828 reflects moderate response variability, suggesting that while the mean indicates agreement, there is a range of opinions regarding usefulness. Negative skewness (-1.312) indicates a slight leftward skew, implying that more respondents strongly agreed with the construct. The 2.548 kurtosis suggests a moderately peaked distribution, potentially with some outliers, in the responses regarding perceived usefulness.

4.5.2 *Perceived Ease of Use (PEU)*

With a mean of 3.932, the data suggest that respondents, on average, found AI-powered tools relatively easy to use. The standard deviation of 0.750 demonstrates moderate variability in the responses. A negative skewness of -0.984 implies a leftward skew, indicating a tendency for respondents to agree with ease of use. The 1.521 kurtosis signifies a moderately peaked distribution, potentially indicating a higher concentration of responses around the mean.

4.5.3 *Perceived Information Effectiveness (PIE)*

The mean score for PIE is 3.407, suggesting that, on average, respondents had a positive perception of the effectiveness of AI tools' information in academic research. The standard deviation of 0.772 reflects moderate variability in responses. The negative skewness (-0.563) indicates a slight leftward skew, showing a tendency towards agreement regarding information effectiveness. The kurtosis of 0.333 suggests a distribution with fewer extreme values.

4.5.4 *Prior Knowledge and Awareness (PKA)*

Respondents with a mean of 3.753 generally exhibited positive prior knowledge and awareness of AI tools for research purposes. The standard deviation of 0.700 indicates moderate variability. The negative skewness of -0.659 suggests a leftward skew, and the respondents tend to agree with their prior knowledge. The kurtosis of 1.146 implies a moderately peaked distribution.

4.5.5 *Attitude Towards Use (ATU)*

The mean score for ATU is 3.994, indicating a positive attitude towards using AI tools in academic research, and respondents, on average, showed agreement. The standard deviation of 0.693 suggests moderate variability in attitudes. A negative skewness of -0.534 implies a leftward skew, indicating a stronger tendency toward agreement. The kurtosis of 0.063 suggests a distribution with a relatively flat peak.

4.5.6 *Actual Adoption (AA)*

With a mean of 3.757, the data indicate that respondents, on average, leaned towards the actual adoption of AI tools in their academic research. The standard deviation of 0.820 shows a moderate level of variability. A negative skewness of -0.710 suggests a leftward skew, indicating a stronger tendency toward agreement with actual adoption. The kurtosis of 0.586 implies a moderately peaked distribution, potentially with some outliers.

4.5.7 *Trust (TR)*

The mean score for TR is 3.344, which indicates a moderately positive level of trust in AI tools for academic research. The standard deviation of 0.876 reflects moderate variability in trust levels. A negative skewness of -0.442 implies a leftward skew, indicating a tendency towards agreement with trust. The kurtosis of -0.376 suggests a distribution with a relatively flat peak.

4.5.8 *Self-Efficacy (SE)*

With a mean of 3.883, respondents, on average, expressed a relatively high degree of self-efficacy in using AI tools for academic research. The standard deviation of 0.597 shows relatively low variability in self-efficacy scores. A negative skewness of -0.357 indicates a leftward skew, suggesting that respondents generally felt confident in their self-efficacy.

4.5.9 *Social Influence (SI)*

The mean score for SI is 3.331, indicating that the respondents, on average, exhibited a moderately positive perception of social influence in using AI tools for academic research. The standard deviation of 0.825 reflects moderate variability in responses to social influence. A negative skewness of -0.303 suggests a leftward skew, with respondents tending to agree with the influence factor. The kurtosis of -0.304 implies a distribution with a relatively flat peak.

An examination of specific descriptive statistics provides further insights into the distribution characteristics of the variables. For instance, the mean score for SI is calculated at 3.331, indicating that, on average, respondents harboured a moderately positive perception of social influence in their utilisation of AI tools for academic research. The standard deviation, recorded at 0.825, signifies moderate variability in responses to social influence among the respondents. Furthermore, it is also noted that the negative skewness value of -0.303 suggests a leftward skew in the distribution, indicating that respondents tended to agree more with the influence

factor. Moreover, the kurtosis value of -0.304 indicates a distribution with a relatively flat peak, suggesting that the data exhibit fewer extreme outliers or deviations from the mean compared to a normal distribution.

4.6 Correlation Analysis

This section presents and discusses the results of the correlation analysis, which constitutes an important step in investigating the relationships between the constructs under study. Spearman's rho was employed as the chosen statistical method due to the nonnormal distribution of the data, ensuring that nonparametric tests are used (Field, 2018). The focus is on attitude towards use and its correlations with independent constructs: perceived usefulness, perceived ease of use, perceived information effectiveness, and prior knowledge and awareness. Therefore, correlation analysis was used to assess the direction and strength of the relationships between the dependent variable (ATU) and the independent variables.

Furthermore, the correlation analysis extended its scope to include the relationship between the attitude towards use and actual adoption. This analysis evaluated how students' attitudes translate into the actual utilisation of AI tools.

The correlation analysis also served as a mechanism for identifying potential multicollinearity issues between independent variables (Salvatore, 2021). Therefore, in addition to the relationships between the dependent and independent variables, the correlation matrix was also used to assess the relationships between the independent variables. This step was important as it laid the groundwork for the forthcoming multivariate linear regression analysis, ensuring the precision and validity of the multiple linear regression model. The following table summarises the results of the correlation analysis conducted.

Table 4.5 Correlation analysis

	ATU	PU	PEU	PIE	PKA	AA	TR	SE	SI
ATU	1.00								
PU	.555**	1.00							
PEU	.504**	.529**	1.00						
PIE	.288**	.293**	.409**	1.00					
PKA	.498**	.322**	.367**	.358**	1.00				
AA	.595**	.449**	.433**	.462**	.413**	1.00			
TR	.188**	.126*	.215**	.609**	.268**	.405**	1.00		
SE	.537**	.400**	.497**	.308**	.365**	.461**	.259**	1.00	
SI	.150*	.078	.103	.404**	.281**	.270**	.553**	.254**	1.00

***. The correlation is significant at the 0.01 level (2-tailed).*

**. The correlation is significant at the 0.05 level (2-tailed).*

The results show that ATU positively correlates with all other independent variables, albeit with different strengths. It is shown that the attitude toward use correlates

significantly with perceived usefulness, perceived ease of use, perceived effectiveness of information, prior knowledge and awareness, and social influence. A significant positive and medium relationship exists between the attitude toward use and actual adoption (rho=0.595). However, correlation analysis results do not reveal the causal relationship among the variables; hence, further analysis was conducted to test the various hypotheses formulated.

The correlation results also show that there are no highly correlated independent variables. Serious multicollinearity problems, such as indeterminate or invalid estimates of coefficients, arise if the correlation coefficient between independent variables is more significant than 0.8 in absolute terms (Field, 2018). Therefore, there was no severe multicollinearity problem in this case since all correlation coefficients were less than 0.8, suggesting that independent variables can be used in a multivariate regression model without causing problems with the model's validity. The following section focuses on regression analysis.

The following section focuses on regression analysis.

4.7 Regression analysis

Multiple linear regression analysis assessed the influence of independent variables (perceived usefulness, perceived ease of use, perceived information effectiveness, prior knowledge and awareness, and social influence) on the attitude towards use. Furthermore, the regression analysis also determined how attitudes towards use affect the adoption of the AI tools.

4.7.1 *Drivers of attitude towards use*

A multiple linear regression model was estimated, with an attitude towards use as the dependent variable. Independent variables included perceived usefulness, ease of use, information effectiveness, prior knowledge and awareness, and social influence. The model summary is shown in Table 4.6.

Table 4.6 Model Summary: Drivers of attitude towards use

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.648[a]	.420	.409	.533
a. Predictors: (Constant), SI, PEU, PKA, PU, PIE				

The multiple linear regression model reveals an R-squared value of 0.420, indicating that approximately 42% of the variance in Attitude Toward Use (ATU) can be explained by the combined influence of the independent variables: Perceived Usefulness (PU), Perceived Ease of Use (PEU), Perceived Information Effectiveness (PIE), Prior Knowledge and Awareness (PKA), and Social Influence (SI). This moderate R-squared value signifies that these independent variables notably impact students' attitudes towards using AI tools for academic research. The general validity of the model is presented below.

Table 4.7 Analysis of variance

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	50.336	5	10.067	35.406	.000[b]
	Residual	69.377	244	.284		
	Total	119.712	249			
a. Dependent Variable: ATU						
b. Predictors: (Constant), SI, PEU, PKA, PU, PIE						

The ANOVA results present a significant statistic of the F test of 35.406 ($p < .001$). This indicates that the overall regression model is valid and provides valuable insights into the collective impact of the independent variables on the attitude towards use. The model demonstrates a significant ability to explain the variance in ATU, underlining its overall statistical significance. The influence of each of the independent variables is summarised in Table 4.8.

Table 4.8 Regression coefficients

Model		Unstandardised Coefficients		Standardised Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.027	.242		4.250	.000
	PU	.285	.049	.340	5.819	.000
	PEU	.142	.058	.154	2.459	.015
	PIE	.029	.055	.032	.526	.599
	PKA	.321	.055	.324	5.815	.000
	SI	-.006	.046	-.008	-.140	.889
a. Dependent Variable: ATU						

The regression results show that the Perceived Usefulness (PU) coefficient is both positive and highly statistically significant ($\beta = 0.340$, $p < .001$). This indicates that PU significantly influences students' attitudes towards using AI tools for academic

research. A higher perception of usefulness is associated with a more positive attitude.

Perceived Ease of Use (PEU) also significantly influences ATU (β = 0.154, p = 0.015). While the effect is positive, it is relatively minor compared to PU. Students who find AI tools easy to use tend to have a more favourable attitude towards use.

Furthermore, the coefficient for Prior Knowledge and Awareness (PKA) is both positive and highly statistically significant (β = 0.324, p < .001). This implies that PKA significantly affects ATU. Students with higher prior knowledge and awareness are likelier to have a positive attitude towards using AI tools.

However, the coefficients of Social Influence (SI) and Perceived Information Effectiveness (PIE) are not statistically significant (p >0.05). This suggests that these factors do not substantially shape students' attitudes towards AI tool use.

4.7.2 *Attitude towards use and Actual Adoption of AI tools*

This section analyses the extent to which students' attitude towards using AI tools influences the actual adoption of the tools in academic research. A simple regression model was estimated, with actual adoption (AA) as the dependent variable and attitude towards use as the independent variable. A control variable, age, was also included in the model to control for the influence of age in adopting AI tools. Age was transformed into a dummy variable, with 1 being students under the age of 40 and 0 being students above the age of 40. The model summary is reported below.

Table 4.9 Model summary: ATT and AA

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.622[a]	.387	.382	.645
a. Predictors: (Constant), Below40, ATU				

The model summary reveals an R-squared value of 0.387, indicating that approximately 38.7% of the variance in actual adoption can be explained by the student's attitude towards use and the control variable, age. The validity of the whole model is summarised below:

Table 4.10 Analysis of variance: ATT and AA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	64.785	2	32.392	77.826	.000[b]
	Residual	102.806	247	.416		
	Total	167.591	249			
a. Dependent Variable: AA						
b. Predictors: (Constant), Below, ATU						

The ANOVA results indicate a highly significant statistic of the F test of 77.826 ($p < .001$). This demonstrates that the overall regression model is valid and statistically significant. The regression coefficients are reported in the following table:

Table 4.11 Regression coefficients

Model		Unstandardised Coefficients		Standardised Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.808	.240		3.368	.001
	ATU	.732	.059	.619	12.41	.000
	Below 40	.064	.084	.038	.763	.446
a. Dependent Variable: AA						

The coefficient for Attitude Towards Use (ATU) is positive and statistically significant ($\beta = 0.619$, $p < .001$). Students' attitudes significantly influence their adoption of AI tools in academic research. A positive attitude is associated with a higher likelihood of adopting these tools.

However, the coefficient for the dummy variable below 40, representing students under 40 years of age, is not statistically significant ($\beta = 0.038$, $p > 0.05$). This suggests that age does not exert a considerable influence on the actual adoption of AI tools.

These results indicate that the students' attitudes are pivotal in adopting AI tools.

4.8 Moderation Analysis

The study also conducted a moderation analysis to assess whether the relationship between the attitude towards use and actual adoption is moderated by the student's trust in the AI tool (TR) or moderated by self-efficacy (SE). Therefore, trust and self-efficacy were the two moderator variables. The moderation role of each was analysed. To conduct moderation, the interaction variables were calculated by multiplying the moderator and independent variables (Field, 2018). This means that the attitude towards use was multiplied by trust to produce a new variable (ATUxTR). Attitude towards use was also multiplied by self-efficacy to produce a new variable (ATUxSE). Then, a hierarchical regression model was estimated to assess the change in the model's predictive power (R-square) because of the inclusion of the moderator variable. The results are presented in the following sections.

4.8.1 *ATU and TR*

In the first step, attitudes towards use and trust were entered as independent variables, with actual adoption as the dependent variable. The interaction variable (ATUxTR) and the independent variables were entered in the second step. The change in R-square was then assessed. The results are as follows:

Table 4.12 Moderation analysis: ATU and TR

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.680[a]	.462	.458	.604	.462	106.165	2	247	.000

2	.691[b]	.477	.471	.596	.015	7.171	1	246	.008
a. Predictors: (Constant), TR, ATU									
b. Predictors: (constant), TR, ATU, ATU_TR									

In the first step of the analysis, when ATU and TR were entered as independent variables, the model explained 46.2% of the variance in Actual Adoption (AA). The interaction variable (ATUxTR) and the existing independent variables were introduced in the second step. This step resulted in a significant change in R-square ($\Delta R^2 = 0.015$, $p = 0.008$). This signifies that the moderator variable significantly contributes to the model's predictive power. Therefore, the significant change in the R-square implies that trust significantly moderates the relationship between attitude towards the use and actual adoption of AI tools.

4.8.2 *ATU and SE*

In the first step, attitudes towards use and self-efficacy were entered as independent variables, with actual adoption as the dependent variable. The interaction variable (ATUxSE) and the independent variables were entered in the second step. The change in R-square was then assessed. The results are as follows:

Table 4.13 Moderation analysis: ATU and SE

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.634[a]	.402	.397	.636	.402	83.038	2	247	.000
2	.895[b]	.801	.799	.368	.399	493.656	1	246	.000
a. Predictors: (Constant), SE, ATU									
b. Predictors: (constant), SE, ATU, ATU_SE									

In the first step of the analysis, where ATU and SE were both entered as independent variables, the model accounted for 40.2% of the variance in Actual Adoption (AA). The interaction variable (ATUxSE) was included alongside the existing independent variables in the second step. This step resulted in a substantial and statistically significant change in the R-square ($\Delta R^2 = 0.399$, $p < 0.001$). Introducing Self-Efficacy (SE) as a moderator significantly improves the model's ability to predict adoption. This indicates that the relationship between actual adoption and attitude towards use is influenced by self-efficacy.

4.9 Hypotheses Results

H1: The perceived usefulness of AI-powered tools significantly determines the attitude towards usage.

Regression analysis was conducted to test this hypothesis. The results revealed that the perceived usefulness coefficient was positive and statistically significant ($\beta = 0.340$, $p < .001$). The result indicates that perceived usefulness significantly influences students' attitudes towards using AI tools for academic research. This concludes that the students' higher perception of the usefulness of AI tools is associated with a more positive attitude toward their use. Therefore, Hypothesis 1 was supported by the results.

H2: Perceived ease of use of AI-powered tools significantly determines the attitude toward use.

This study hypothesised that students' perceived ease of use of AI-powered tools significantly determines their attitude towards using the tool. Regression results revealed that perceived ease significantly influenced attitude towards use ($\beta = 0.154$, $p = 0.015$). This suggests that students who find AI tools easy to use tend to have a more favourable attitude towards use. Therefore, hypothesis two was supported in this study.

H3: Perceived effectiveness of information generated by AI-powered tools significantly determines the attitude toward use.

It was also hypothesised that the attitude towards using AI tools was determined by the perceived effectiveness of the information generated by the tool. The hypothesis was tested using regression analysis. The results revealed that the coefficient of perceived information effectiveness was statistically insignificant ($p>0.05$). This suggests that perceived information effectiveness does not determine the attitude towards using AI tools. Therefore, Hypothesis 3 was not supported.

H4: Prior knowledge and awareness of AI-powered tools significantly determine the attitude toward use.

The fourth hypothesis was that the student's previous knowledge and awareness of the tool influenced their attitude towards using AI tools. Regression analysis was used to test this hypothesis, and the results showed that the coefficient of prior knowledge and awareness was positive and statistically significant ($\beta = 0.324$, $p < .001$). This implies that prior knowledge and awareness significantly affect attitude towards use. Students with higher prior knowledge and awareness are likelier to have a positive attitude towards using AI tools. Therefore, Hypothesis 4 was supported.

H5: Social influence significantly determines the attitude towards using AI tools.

This study hypothesised that social influence determines students' attitudes toward using AI tools. Results revealed that the coefficient of social influence was not statistically significant ($p>.05$). This suggests that there was no evidence to support the hypothesis that social influence plays a role in shaping students' attitudes towards AI tool usage. Therefore, the hypothesis was not supported in this study.

H6: Students' attitude towards using AI-powered tools significantly determines adoption.

The study also specified the hypothesis that the student's attitude towards using AI-powered tools would, in turn, influence the actual adoption of the tool. A regression model was estimated to test this hypothesis. The results revealed that the coefficient of attitude toward use was positive and statistically significant ($\beta = 0.619$, $p < .001$). This signifies that students' attitudes significantly influence their adoption of AI tools in academic research. A positive attitude is associated with a greater likelihood of adopting these tools. Therefore, Hypothesis 6 was supported.

H7: Trust in AI tools moderates the relationship between attitude towards AI usage and actual adoption.

It was further hypothesised that trust in AI tools would moderate the relationship between attitude towards AI usage and actual adoption. Evidence from the moderation analysis showed a statistically significant change in the model's

predictive power when the moderator variable was added ($\Delta R^2 = 0.015$, $p = 0.008$). This suggests that student trust in the AI tool significantly influences the relationship between attitude towards using the AI tool and actual adoption of the tools. Therefore, Hypothesis 7 was supported.

H8: The student's self-efficacy moderates the relationship between attitude towards AI usage and actual adoption.

Finally, the hypothesis posited that the student's level of self-efficacy would influence the association between attitude towards AI usage and its actual adoption.

The moderation analysis results showed a significant change in the model's predictive power as the moderator variable was added ($\Delta R^2 = 0.399$, $p < 0.001$). This suggests that a student's self-efficacy plays a crucial role in influencing the relationship between attitude towards using and adopting the AI tool. Therefore, Hypothesis 8 was supported.

4.10 Chapter Summary

In this chapter, an analysis of the drivers of the adoption of AI tools was performed. The chapter first presented an overview of the sample's demographic characteristics, which consisted of Wits University students doing academic research. A final sample of 250 students was used. To assess the reliability of the measurement scales used in this study, it was essential to evaluate the internal consistency of the scales using Cronbach's alpha coefficient. All measurement scales were confirmed to be highly reliable and were used for further analysis in this study. Normality tests were conducted to determine the nature of the data used, and it was revealed that the data deviated from the normal distribution. Therefore, nonparametric tests were conducted. Furthermore, the chapter presented descriptive statistics of the variables to understand the data characteristics used. Correlation analysis was also performed to test the strengths and direction of the relationships between variables.

The hypotheses were tested using multiple linear regression and moderation analysis. Results revealed that the main drivers of AI adoption among Wits University students were the tool's perceived usefulness, ease of use, and prior knowledge and awareness. It was also shown that students with a positive attitude towards using AI tools were highly likely to adopt them in their academic research. Furthermore, the results revealed that trust and self-efficacy play a crucial role in influencing the relationship between attitude towards using AI tools and the actual adoption of the tools. A detailed discussion of these results is provided in the following chapter.

CHAPTER 5. DISCUSSION OF RESULTS

5.1 Introduction

In contemporary academia, the dynamic integration of Artificial Intelligence (AI) tools across diverse research domains stands as a notable trend. This phenomenon underscores the pressing need for educators and policymakers to comprehend the intricate factors that shape students' attitudes and adoption of AI-powered tools. Consequently, this chapter embarks on a scholarly inquiry, conducting an in-depth analysis of research findings with the objective of unveiling the determinants that influence students' perceptions and behaviours concerning using AI tools in academic environments. Therefore, this chapter discusses the research results of the literature. The previous findings for each hypothesis will be compared and argued based on the current findings.

5.2 Perceived Usefulness

The study hypothesised that the perceived usefulness of AI-powered tools significantly determines the attitude towards usage by students conducting academic research, and this hypothesis was supported. This agrees with Butt et al. (2021), who found that students who perceived AI-powered story bots as helpful in learning a second language had a positive attitude towards using bots and were ultimately able to achieve their goals.

Furthermore, most researchers found that when students find the AI tool or valuable technology in the tasks at hand, their behavioural intention is positively influenced to adopt the technology (Al-Rahmi et al., 2020; Al Shamsi et al., 2022; Oyetade et al., 2020; Sitthipon et al., 2022). This could be because these tools can significantly enhance the research experience, making the execution of research tasks more effective, engaging, and easy to access the resources. However, Tahar et al. (2020) suggested that understanding the usefulness of a technology tool is not

straightforward, which may affect its adoption. This is sometimes caused by the complexities in the design and the lack of user friendliness of the tool.

This study confirmed that students find AI-powered tools useful in their academic research tasks, and thus, their attitude towards AI usage is positively influenced. Research students' benefits influence this using the tools (Kuleto et al., 2021).

5.3 Perceived Ease of Use

The study hypothesised that perceived ease of use of AI-powered tools significantly determines attitude towards the use of tools by students who do academic research. Research results have supported this hypothesis. This finding agrees with other researchers who found that when students find it easy to use technology, their attitude and behavioural intention are positively impacted, resulting in the adoption of technology (Başaran & Hussein, 2023; Kashive et al., 2021; Sun & Gao, 2020; Teo et al., 2019). This could be due to a high level of confidence that students may have in using the tools, caused by the intuitive interface, which makes the learning curve to use the tool quicker and more effective for its intended purposes. Furthermore, positive recommendations from peers based on their experience and sharing how the tools work may result in students finding the tools easy to use.

Therefore, since AI tools are available on the internet, their ease of use is bound to influence adoption; hence, the hypothesis that perceived ease of use significantly impacts attitudes towards adoption was proven to be true.

5.4 Perceived effectiveness of AI generated information

It was found that the hypothesis that the perceived effectiveness of information generated by AI-powered tools significantly determines attitude towards usage is not supported by students. This agrees with Kashive et al. (2021) and Sumakul et al. (2022) that students notice that, in some instances, the information produced by AI has drawbacks. However, this ineffectiveness of information does not impact their

attitude towards using the tools. Instead, it allows them to apply critical thinking skills and creativity.

This study confirmed that the effectiveness of information generated by AI tools is not a determining factor in adopting the tools. Students use AI tools based on the benefits they derive from utilising them, such as summarising multiple articles, saving time on editing, and triggering critical thinking, to mention a few.

5.5 Prior Knowledge and Awareness of AI Tools

The hypothesis, prior knowledge, and awareness of AI-powered tools significantly determine attitudes towards usage by students who are conducting research. Thus, this was supported by the results. This agrees with Tlili et al. (2023) who found that awareness of the AI tool leads to practical usage, implying that the user has a positive attitude towards use. This could be because students with prior knowledge and awareness of AI tools are more likely to recognise the potential benefits, such as improved efficiency and accuracy compared to traditional research methods. Students who are familiar with tools are more likely to understand the tool's capabilities, such as data analysis, summarizing articles, paraphrasing, and grammatical corrections, thereby leading to a positive attitude towards usage.

This is further supported by Susnjak (2022) in that knowledge of AI tools equips a student to execute tasks, use the tools efficiently, and understand the tools' limitations (Tlili et al., 2023). This hypothesis disagrees with (Chang et al., 2022), who asserted that prior knowledge and awareness about AI tools are not critical in driving adoption because these tools are meant to deliver information that a student requires without previous knowledge. This means that sharing information about the tools available that can be used to assist students in their research would eliminate fear and anxiety, as mentioned by Kashive et al. (2021), and promote adoption (Kuleto et al., 2021).

5.6 Social Influence

This study hypothesised that social influence determines students' attitudes towards using AI tools. The results of the study did not support this hypothesis. These results agree with (Abbad, 2021; Alshammari, 2021; Andrews et al., 2021), who found that social influence does not positively impact the behaviour of adopting the technology. The results disagreed with the findings by Alomari and Jabr (2020), who stated that a positive attitude towards AI usage is associated with increased motivation by people who matter to an individual. Sometimes, students may have unique preferences, such as sticking to traditional methods of conducting research as opposed to adopting tools that their peers are utilising. Furthermore, social influence as a predictor of student behavioural intention towards the use of the technology, as per (Alasmari & Zhang, 2019; Alhwaiti, 2023), was not supported. Although tools are readily available and easy to access, students might be more inclined to use them based on convenience rather than social influence. Therefore, social influence is not a driver for utilising AI-powered tools.

5.7 Attitude Towards AI tools

The study's results supported that students' attitude towards AI-powered tools significantly determines adoption. This is in line with the findings of Henderson et al. (2017) and Naveh and Shelef (2021) in that factors such as usefulness and ease of use positively impact an individual's attitude to utilise the technology. This is mainly based on the benefits that the individual derives from the tool, such as enhanced learning outcomes and academic performance (Alomari & Jabr, 2020; Lee et al., 2022). Furthermore, the overall tool’s functionality which is aligned with the individual’s needs and goals, enhances a positive attitude, making it easier to integrate the tools into existing research processes.

5.8 Trust as a Moderating Factor

The study further hypothesised that the relationship between attitude towards usage and actual adoption of AI-powered tools is moderated by trust. The results supported this hypothesis. This affirms the findings by (Chang et al., 2022; Choi et al., 2022) that when students trust the technology, they are more likely to use it in their academic endeavours. Trust was also found to be the strongest predictor of students' behavioural intentions (Kelly et al., 2023; Wang, 2020). When students trust that an AI tool is less prone to errors, they are more likely to adopt it, irrespective of occasional mistakes that may occur. Furthermore, trust is enhanced when the AI tool discloses how it complies with relevant data protection regulations and ethical standards. This is what is seen with the enforcement of data privacy regulations and policies that most technology has to put users at ease as to how their offered technology complies. Failure to disclose how a particular tool ensures data privacy and adheres to regulations may negatively affect attitudes towards adoption. Therefore, trust is one of the moderators of adopting AI-powered tools in academic research.

5.9 Self-efficacy as a Moderating Factor

Lastly, it was hypothesised that the relationship between attitude towards AI usage and actual adoption is moderated by student self-efficacy, which was supported by this study. This agrees with (Kelly et al., 2023; Mhlanga, 2023; Ostheimer et al., 2021), who found that high self-efficacy leads to a positive attitude towards the usage of a tool, thereby positively influencing adoption. Self-efficacy influences individuals' confidence in their ability to learn how to use a tool and take risks, leading to a proactive and adaptive approach to adopting AI tools. On the contrary, this study suggests that students with low self-efficacy may find it challenging to adopt the tools, and this agrees with (Yilmaz & Yilmaz, 2023). Having low self-efficacy may make a student, after having a negative experience with a tool, dismiss the possibility of gaining benefits because of a lack of intrinsic motivation. Students with low self-

efficacy may end up not realising the benefits that are experienced by students with high self-efficacy, affecting the adoption rate of AI tools.

5.10 Chapter Summary

This chapter discussed the findings of this study compared to previous studies. Most of the findings were shown to align with other researchers. The study found that the drivers of using AI tools by university students in South Africa conducting research are perceived usefulness, perceived ease of use, and having knowledge and awareness about the tools, which leads to a positive attitude towards using tools. This means that when the tools are easy to navigate and interact with, and there are benefits realised, such as meeting objectives, finishing tasks quicker and being able to be creative even when there are errors in the information generated by AI, the student's attitude towards using the tools is positively impacted. Prior knowledge of AI tools positively affects attitude, as the user would know how to scrutinise the information generated and enhance their approach to executing tasks.

This study also agreed with most authors that people in one's circle (social influence) do not necessarily influence their attitude towards using tools. Therefore, students use tools when they anticipate that their needs will be met.

Trust and self-efficacy are factors that moderate the attitude towards use. This means that even when PU, PEOU, and prior knowledge of tools positively lead to a positive attitude towards using tools, a person will use the tool when they trust and have confidence in how to use it.

CHAPTER 6. CONCLUSIONS AND RECOMMENDATIONS

6.1 Introduction

This research study examined the drivers of university students using AI-powered tools when conducting academic research in South Africa. The PU and PEOU from TAM (Davis, 1989) were tested as the determinants of a positive attitude towards adoption. Furthermore, other factors such as perceived effectiveness of information, prior knowledge and awareness and social influence as per Venkatesh et al. (2003) were researched as factors that positively impact the attitude to use the tools. From these extended factors, prior knowledge and awareness were the only factors found to positively affect attitude. Trust and self-efficacy were researched as moderators for actual usage since other authors suggested that there are privacy, biases, and hallucination issues that are presented by AI (Choi et al., 2022; Lund et al., 2023; Yeh et al., 2021).

6.2 Key Drivers Of University Students' Utilisation of AI-Powered Tools

A positive attitude towards using a particular AI-powered tool was found to be driven by perceived usefulness, perceived ease of use, prior knowledge, and awareness about the tool, and this is moderated by trust and self-efficacy. The AI tools are helpful since they help students achieve their goals and objectives, such as searching and summarising articles, writing or editing grammar, and making an impartial judgment about articles, which are examples of tasks that AI tools can accomplish (Lund et al., 2023). Therefore, students are influenced to have a positive attitude about using the tool due to the benefits they receive and the tools being easy to navigate and comprehend. However, this is possible when the student has prior knowledge and awareness of the tool. Hence, prior knowledge and awareness also promote a positive attitude towards usage.

Therefore, students are using AI-powered tools since they know and are aware of the tools, which are easy to use, and they are finding the tools useful since they enable students to meet their goals and objectives efficiently. Trust and self-efficacy moderate actual usage. This means that even when a student has knowledge about the tool and find it easy to use and valuable, they will only adopt the tool if they trust and have confidence in using the tools, for example, that their privacy is protected and that there is some level of effectiveness in the tool output.

6.3 Perceived Usefulness and Ease of Use

The tools' perceived usefulness and ease of use contribute to using the AI tools. This means that most students perceive AI tools as applicable to their research studies, and they also think AI tools are easy to use in research. This increases their desire and willingness to use AI tools in their research studies. Furthermore, this suggests that the AI tools are designed with the students in mind and incorporate their needs to fulfil goals. Hence, students adopt the tools as they are helpful and easy to use.

The favourable implication is that student academic research output is more efficient since repetitive tasks such as literature reviews, citations, and editing are automated. This gives the researcher time to focus on interpreting results and developing new or creative ideas, thus reducing the likelihood of human errors. This further suggests that AI tools can be a personalised research assistant to a student by answering questions, offering suggestions for methodologies, and being a guide throughout the research process.

On the other hand, negative implications can be introduced by the usefulness and ease of use of AI tools, such as the lack of skills to effectively use the tools. The results of this study suggested that having prior knowledge and awareness of the available tools leads to a positive attitude towards usage. Therefore, this becomes a barrier and creates a gap between the students who know and those who do not. Another barrier is the cost of advanced AI tools, as not all researchers and universities may have access to them.

Furthermore, the lack of skills would result in the inability to understand the AI algorithm's bias and the tools' ethical usage. While AI-powered tools can significantly benefit research students in both efficiency and precision improvement based on their ease of use and usefulness, they also pose problems that must be addressed to ensure ethical, fair, and successful inclusion in the research process.

6.4 Prior Knowledge and Awareness of AI-Powered Tools

Prior knowledge and awareness about AI-powered tools were found to be one of the drivers towards a positive attitude toward utilisation. This means that when students understand how a tool works and its shortcomings, they are bound to adopt the tools in their academic research and use them efficiently. They will be more confident in rapidly integrating the tools into their research tasks, streamlining the learning curve.

Having prior knowledge and awareness of AI tools enables ease of using AI tools to research tasks, leading to enhanced efficiencies and increased quality of results, productive and timely execution, and completion of tasks. Therefore, knowing how the tools work would equip students with the understanding of how to better use the tools to their advantage.

However, there is a risk that students may be overly focused on AI tools when they have substantial knowledge and awareness of the tools. This may potentially negatively affect research skills and critical thinking. Although prior knowledge and awareness of AI tools lead to positive attitudes and adoption, students must balance and integrate AI tools as complementary rather than substitutes for essential research tasks.

6.5 Perceptions of Whether AI generated Information Impacts Utilisation

AI tools can analyse large datasets quickly, conduct literature reviews more efficiently, and summarise key findings. However, when generated by AI, the output of these tasks can sometimes be inaccurate. In this study, it was found that the

effectiveness of information generated by AI does not lead to a positive attitude towards usage.

This finding suggests that students who use the tools understand their limitations regarding the effectiveness of the information generated. This means that the tools do not replace the research skills and analytical and critical thinking that a student needs to apply when conducting research. Instead, the tools are assisting students in performing mundane and repetitive tasks.

Therefore, it can be concluded that the effectiveness of information from AI is not a driver of use; however, it persuades analytical, critical thinking, and creativeness while eliminating repetitive tasks. Students use the tools based on their ease of use, usefulness, and the benefits they derive from using the tools.

6.6 Study Contributions

The focus of this study was to explore the drivers of utilisation of AI tools among university students who are embarking on research projects in South Africa. The study has established a wide range of factors that influence the adoption of AI tools. The study addresses a significant literature gap by focusing on university students in South Africa. It provides information on the factors that impact AI adoption in a specific geographic and socioeconomic situation. This leads to a more complex understanding of how technology is embraced in different circumstances. In addition to providing additional literature on the adoption of AI by students in a higher education institution, the study provides higher education institutions with actionable recommendations, highlighting the necessity of incorporating AI training into curricula and holding skills-building workshops. These real-world implications guide institutional solutions to promote the efficient and successful use of AI-powered products.

Furthermore, the study adds to the corpus of theoretical work by including the concepts of perceived information efficacy, prior knowledge and awareness, and social influence as determinants of positive attitude towards usage in the TAM. This

update enhances the model's explanatory capacity when considering the usage of AI in academic research. In addition, this study further elaborates on and enlightens stakeholders on specific concepts, creating an opportunity for policymakers, practitioners, and academics to comprehend and implement some of the concepts. For example, it was observed that self-efficacy and trust were significant modifiers in the actual adoption of AI-powered tools. This study emphasises how important it is to gauge students' general trust in technology and their abilities to use it.

In addition, the research identified essential variables that impact students' perceptions of AI adoption. Prior knowledge and awareness of these technologies and their perceived utility and ease of use were found to substantially impact positive attitudes about using AI-powered tools. It also shows that past knowledge and awareness significantly shape positive sentiments about adopting AI tools among university research students. This empirical validation contributes to the literature by demonstrating how awareness and knowledge play a crucial role in adopting new technology.

6.7 Recommendations

The AI phenomenon is growing, and AI tools are easily accessible online. This study has shown that students use AI tools in their research endeavours. Research students utilise these tools because they are helpful and easy to use, and having prior knowledge and awareness about the tools helps in better utilisation. Due to having prior knowledge and awareness about the tools, students can understand that, in some instances, the information generated by AI tends to be inaccurate; hence trusting the tool and being confident about using a tool moderates the actual usage. Based on these findings, the following recommendations are made:

6.7.1 *Higher Education Institutions To Enhance Awareness Programmes*

University students and other academic stakeholders must receive better education on the benefits and accessibility of AI-driven technologies. A lack of awareness could impede the successful integration of these technologies into research methodologies. Academic staff, researchers, and university administrators should also be part of the target audience to enhance the supervision and administrative capacity related to the use of AI tools. This can be done by conducting orientation seminars to promote a cooperative atmosphere and improved comprehension.

The practical implementation of this recommendation involves deliberate efforts by higher education institutions to include AI-driven technologies as part of the various learning processes in the university curriculum. In addition, technology awareness-building programs should be put on the university calendar to emphasise the importance of the process.

6.7.2 *Universities Need to Include AI Education in Research Programs*

Prior knowledge and skills emerged as one of the significant factors influencing the use of AI tools. This is partly a result of the educational and social background of university students. If this is not addressed, it is likely to expand the disparities in research capability between research students. Integrating AI education into the curriculum is essential to equip students with the necessary abilities to manoeuvre through the rapidly evolving technological terrain. The curriculum should provide adequate content and practical skills in all disciplines to ensure that those lacking the skills and less knowledge can catch up. If this is done, graduating students will also be sufficiently prepared to meet the demands of the modern workforce due to this proactive approach.

The curriculum development process must span all disciplines to promote interdisciplinary collaboration. By doing so, students from different fields will understand the cross-cutting nature of AI applications. Students should be given priority when it comes to practical workshops and projects that allow them to apply AI tools in real-world situations, including research. This would help to improve their ability to acquire skills and solidify their theoretical understanding.

In addition, higher education institutions have the alternative to provide specialised learning tracks to students who choose to pursue the in-depth use of AI tools. This helps to create personalised learning pathways aligned to each student's career goals. To ensure practical implementation of this recommendation, the curriculum assessment process should include a component of theoretical and practical understanding of AI technologies.

6.7.3 *Emphasise Advantages Beyond Information Effectiveness*

This study has shown that the effectiveness of information generated by AI tools does not play a role in determining the utilisation of AI tools. Benefits beyond information effectiveness must be highlighted to guard against lack of utilisation due to misjudgement of information effectiveness. It is critical to highlight the advantages of using AI-powered tools in academic research beyond their information-based efficacy. By presenting a variety of benefits, students can understand the multifarious effects of AI tools. For example, there is a need to demonstrate how AI tools can accelerate research procedures by saving time on data analysis, literature reviews, and text summation, among other duties. Therefore, when users become aware of efficiency improvements, it is anticipated that the use of AI among students will expand.

In addition, the efficiency and time savings issues should be emphasised, drawing attention to situations in which AI tools inspire students to think critically and explore creatively, pushing them to become more involved in their studies. Users are expected to view AI technologies as an addition to their intellectual contributions, not as a replacement for them.

To facilitate the practical implementation of this recommendation, the curriculum should include content on AI-driven technologies, and in that context, the benefits of AI beyond information effectiveness are highlighted. Deliberate practical exercises to demonstrate how to analyse and test the information generated by AI should be designed and implemented.

6.7.4 *Continuous Evaluation and Feedback by Students and other Stakeholders*

This study has shown that there are several drivers for the use of AI tools by research students. The absence of these drivers creates barriers to the use of AI tools. Evaluation feedback and improvement become necessary to enhance the drivers and decapitate the barriers. This can be achieved through an ongoing evaluation and feedback programme. This methodical approach facilitates continuous enhancements, overcomes obstacles, and ensures the implementation is in sync with the user requirements. Universities may establish frequent user surveys by polling research students regularly to get their opinions on AI tools. The use of ongoing evaluation and feedback will be anticipated to provide important information on user satisfaction, difficulties encountered, and opportunities for improvement. In addition, establishing user feedback platforms may help create dedicated online environments for users to provide real-time feedback on their interaction with AI tools. This helps facilitate direct communication and promote engagement. Furthermore, this will create an environment where there is shared experience leading to ease of learning from one another.

To ensure practical implementation of this recommendation, a system should be designed to ensure that before students view their results on the portal, they complete a small survey regarding AI tools used during research. This makes it mandatory for every student to have a say regarding AI-driven technologies used for research within the institution.

Implementing these recommendations is expected to create a conducive environment for successfully adopting AI-powered tools in academic research among South African university students. The proposed actions aim to address the factors influencing attitude and adoption, fostering a positive and supportive ecosystem for integrating AI technologies in research practices.

6.8 Limitations and Suggestions for Further Research

Although this study has provided important information on the drivers of university students' use of AI tools, much more can be done to improve the quality of the results and build knowledge and understanding in the subject area. Some limitations need to be addressed in future research. For example, this study used only the quantitative approach, which is biased towards the positivist paradigm. It lacks in-depth analysis of individual experiences with AI tools. The complex qualitative facets of people's attitudes and experiences were missed. However, they enhance the overall knowledge of the factors that encourage and hinder the adoption of AI by adding nuance and context to quantitative findings. A more robust mixed methods approach, which captures both qualitative and quantitative data, can be adopted by future research on the subject matter.

The study's exclusive emphasis on South African university students as well as on one university limited the applicability of its conclusions to other contexts. To offer a more comprehensive understanding of the factors influencing the adoption of AI in academic research, future studies should investigate a range of geographic situations and different types of higher education institutions. Scholars can perform cross-regional comparative analyses to investigate cultural, institutional, and contextual differences in adopting AI-driven technologies. This would help develop a more sophisticated understanding of the variables that affect adoption in various contexts.

Ethical issues in adopting and utilising AI tools are critical, but this study did not focus on them. Future studies should also add this component for completeness in understanding the drivers and barriers to student adoption and use of AI tools.

Convenience sampling from the University of Witwatersrand was used in the data-gathering process; selection bias has been introduced. This may affect the representativeness of the data sets used in this study and the quality of the results. To ensure the inclusion of a broader spectrum of individuals, future research should use a more robust sampling technique to ensure that different disciplines and

faculties are well represented. This would give a more realistic representation of the population and improve the external validity of the findings.

Although trust and self-efficacy were examined in the study as moderators, additional moderating elements could exist. Further studies should look at other factors to provide a more complete picture of the adoption process, such as institutional support or technological infrastructure.

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APPENDIX A Research Instrument

Wits Business School

Master of Management in Digital Business Research Survey

My name is Danisile Ngomane. I am a Master of Management student in Digital Business at Wits Business School. I am conducting a research study on Drivers of the use of AI – powered tools in academic research: A study of university students in South Africa; under the supervision of Prof Thomas Anning.

I am inviting you to participate in this research survey by answering an online questionnaire that will take an estimated 10 minutes.

Confidentiality Clause

Participation in this survey is entirely optional. All information you enter will be kept strictly confidential. Your replies will be used purely for research purposes and will be shared in aggregate form, preserving your anonymity. There will be no personal identities in any publications or reports coming from this research. You may be guaranteed that your privacy and confidentiality are of my highest concern. Please note that you may leave the survey at any point without fear of being penalised. Giving consent implies that you are over the age of 18.



SECTION A: DEMOGRAPHIC INFORMATION

A1. Please indicate your gender

Male	1
Female	2
Other	3
Prefer not to say	4

A2. Please indicate your current level of study

Undergraduate	1
Honours	2

Masters	3
Doctorate	4

A3. Please indicate the tool that you use in your research tasks.

ChatGPT	1
Bing.ai	2
Google Bard	3
Grammarly	4
Quillbot	5
Scite	6
Litmaps	7
Other	Please state the name

SECTION B

Each question will have a 5-point Likert scale where a participant may indicate the extent to which they agree or disagree with the statement by ticking the corresponding number in the 5-point Likert scale.

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

Perceived Usefulness

Item	**Question/Measurement**	**1**	**2**	**3**	**4**	**5**
PU1	1. I think using AI tools can improve my productivity					
PU2	2. I think using AI tools can improve my performance					
PU3	3. I think using AI tools can encourage me to finish my tasks quickly					
PU4	4. I think using AI tools positively impact my learning outcomes					
PU5	5. I think using AI tools can help me to complete my tasks					

Perceived Ease of Use

Item	Question/Measurement	1	2	3	4	5
PEOU1	6. Learning how to use AI tools is easy to me					
PEOU2	7. My interaction with AI tools is clear and understandable					
PEOU3	8. I find AI tools to be easy to use					
PEOU4	9. I find the user interface of the AI tools easy to navigate					
PEOU5	10. Using AI tools feels effortless and intuitive					

Perceived Information Effectiveness

Item	Question/Measurement	1	2	3	4	5
PIE1	11. I find information generated by AI tools accurate					
PIE2	12. I find information generated by AI tools reliable					

PIE3	13. I find that information generated by AI tools is from trustworthy sources					
PIE4	14. I find that AI tools generate all the necessary information I need					
PIE5	15. I find the information generated by AI tools relevant to my needs					

Prior Knowledge & Awareness

Item	**Question/Measurement**	**1**	**2**	**3**	**4**	**5**
PKA1	16. Having prior knowledge and awareness of AI tools helps me use the tools efficiently					
PKA2	17. Having experience with similar AI tools helps me use the tools efficiently					
PKA3	18. Being an expert in using AI tools helps me to use the tools efficiently					
PKA4	19. Being trained on using AI tools helps me to know how to efficiently use AI tools					

PKA5	20. Being familiar with concepts related to AI tools helps me to know how to efficiently use AI tools					

Attitude toward AI tools usage

Item	Question/Measurement	1	2	3	4	5
ATT1	21. I intend to use AI tools in the future					
ATT2	22. I will recommend using AI tools to my friends and family					
ATT3	23. I will keep myself updated with the latest AI tools					
ATT4	24. I believe using AI tools can improve my results					
ATT5	25. I am open to exploring new AI tools					

Actual AI tools adoption

Item	Question/Measurement	1	2	3	4	5

AD1	26. I adopt AI tools in academic research tasks					
AD2	27. I adopt AI tools to improve my final academic results					
AD3	28. I adopt AI tools to improve the quality of my assignments and projects					
AD4	29. I adopt AI tools to positively affect my ability to manage my time effectively					
AD5	30. I adopt AI tools to positively impact my overall academic confidence					

Trust

Item	**Question/Measurement**	**1**	**2**	**3**	**4**	**5**
TR1	31. I trust AI tools to protect my personal information and maintain my privacy					
TR2	32. I trust AI tools to consistently deliver reliable outcomes					
TR3	33. I trust AI tools to provide accurate results or information					

TR4	34. I trust AI tools to be transparent in how they operate					
TR5	35. I trust AI tools to make fair and unbiased decisions					

Self-efficacy

Item	**Question/Measurement**	**1**	**2**	**3**	**4**	**5**
SE1	36. I have confidence in my ability to use AI tools effectively					
SE2	37. Knowing how to use AI tools affects my attitude towards usage and adoption					
SE3	38. I have confidence in learning new AI tools					
SE4	39. I can quickly grasp and utilise new features or functionalities of AI tools					
SE5	40. I can achieve desired outcomes or results through using AI tools					

SI1	41. People who are important to me think that I should use AI tools					
SI2	42. People who influence my behaviour think I should use AI tools					
SI3	43. The seniors in my university are helpful in the use of AI tools					
SI4	44. In general, the university has supported the use of AI tools					
SI5	45. People whose opinions I respect think that I should use AI tools					

THE END - Thank you.

APPENDIX B The participant information sheet

Good day

My name is Danisile Ngomane, and I am currently pursuing a Master of Management of the Digital Business at the University of the Witwatersrand, Johannesburg. Under the guidance of Prof. Thomas Dorson Anning, I am conducting a research study on examining key drivers of efficient use AI tools in academic research, specifically among university students.

I invite you to participate in this study by answering a survey that will take approximately 10 minutes of your time. Rest assured that all responses will be kept confidential and anonymous. Personal information, such as your gender and level of

study, will be required, but nothing that could identify you will be included in the research report.

The data collected will be stored in SPSS for five years, after which it will be deleted. Only the research team will have access to the data. In the future, other researchers may use the data collected in this study, but your personal information will not be used or disclosed.

Participation in this study is entirely voluntary. You may opt-out at any time and do not have to answer any questions you feel uncomfortable with. Participating in the study has no direct benefits, and you will not be compensated.

Please note that there is low risk involved in this research study, but some questions may trigger negative emotions. The results of this study will be published in a research report. Thank you for considering participating in this study. Your contribution is greatly appreciated.

If you have any questions about this research study during or after, please contact me or my supervisor at the details listed below. If you have any concerns or complaints about the ethical procedures of this research study, you are welcome to contact the University Human Research Ethics Committee (Non-Medical), telephone +27(0) 11 717 1408, email hrecnon-medical@wits.ac.za.

Kind Regards

Researcher:

Danisile Ngomane,

Supervisor:

Prof Thomas Dorson Anning, thomas.dorson.anning@wits.ac.za, +27 11 717 8233

APPENDIX C Ethics Clearance

Graduate School of Business Administration
University of the Witwatersrand, Johannesburg

Wits Business School

Wits Business School Ethics Committee
Constituted under the University Human Research Ethics Committee (Non-Medical)

Ethics Clearance Certificate

Ethics protocol number: WBS/DB1153194/395

This certificate is only valid with a legitimate ethics protocol number and signed by the Researcher (below).
This certificate is only valid if permission has been granted by the Registrar's Office of Wits University.

Project title	Drivers of the use of AI-Powered tools in academic research: A study of university students in South Africa
Investigator / Researcher	MS Danisile Priscilla Ngomane
Nature of Project	MM (Digital Business)
Decision of the Committee	Approved, provided stakeholders and participants are guaranteed anonymity and confidentiality.
Issue Date of Certificate	8/29/2023
Expiry date	Date of submission of the project / research report
Chairperson	Dr Pius Oba ☎ +27 11 717 3976 +27 82 733 6587 pius.oba@wits.ac.za

Declaration by Researcher

One copy must be signed by the Researcher and returned to the Chairperson of the Wits Business School Ethics Committee.

I fully understand the conditions under which I am authorized to carry out the abovementioned research and I guarantee to ensure compliance with these conditions. Should any departure to be contemplated from the research procedure as approved I undertake to resubmit the protocol to the Committee.

Signature

30/08/2023
Date:

Confidential