UNIVERSITY OF KWAZULU-NATAL

The acceptance of chatbot technology to support academic activity at the University of KwaZulu-Natal

By

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I, **Ebunoluwa Ehikowoicho Johnson** declare that

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Abstract

Conversational chatbots powered by artificial intelligence (AI) technology have recently become increasingly popular. They have widespread use in various industries, including e-commerce, online banking, and digital healthcare. Users of online systems could receive individualized assistance because of this innovative technology's capabilities. The University of KwaZulu-Natal (UKZN) has strategised to embrace technologies that contribute towards the with the 4th Industrial Revolution (4IR). Aligned to this commitment to 4IR, UKZN has introduced chatbot technology into the domains of university administration and pedagogy.

Student registration at the University of KwaZulu-Natal (UKZN) has been identified as a problem due to low throughput rates often resulting in late registrations that compromise student academic performance. Also, the University is making a concerted effort to embrace a hybrid teaching and learning strategy whereby online learning is used to complement the de facto face to face pedagogical model. Student registration and the gravitation to online learning have been identified as two areas where technological intervention will be beneficial to the University.

The Information and Communication Services (ICS) at UKZN have developed a chatbot named Msizi (commonly referred to as the Msizibot) to provide students with an interactive feature to support the online registration process and the use of the Moodle/Learn2022/23 learning management system (LMS).

Students' intention to adopt and utilize the Msizibot for assistance during online registration and for guidance on using the University's LMS were measured using the UTAUT model as an underpinning theoretical framework. Students at UKZN were polled quantitatively about their use of the Msizibot during the study's empirical phase. UTAUT served as a framework for classifying the data-collection instrument that was employed in the study. Effort Expectancy (EE), Performance Expectancy (PE), and Social Influence (SI), were found to significantly link to students' intention to adopt the Msizibot to assist with online registration and the usage of the LMS. A significant outcome of the study was that the University has to invest in awareness programmes where students are guided on optimising their experience of using Msizibot. This will result in greater throughput rates when it comes to online registration. Also, the Msizibot needs to be advocated as a technology that enhances pedagogy at the University by increasing awareness of its potential to help students to become expert users of the University LMS.

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LIST OF ABBREVIATIONS

4IR	4th Industrial Revolution
AI	Artificial Intelligence
AIML	Artificial Intelligence Markup Language
BI	Behavioural Intention
EC	Ethical Clearance
EE	Effort Expectancy
FC	Facilitating Conditions
HEI	Higher Education Institution
ITSs	Intelligent tutoring systems
NLP	Natural Language Processing
PE	Performance Expectancy
PEOU	Perceived Ease of Use
PU	Perceived Usefulness
SI	Social Influence
SPSS	Software for the Social Sciences
TAM	Technology Acceptance Model
TPB	Theory of Planned Behavior
UKZN	University of KwaZulu Natal
UTAUT	Unified Theory of Acceptance and Use of Technology

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Chapter 1– Introduction and Overview of Research

1.1 Introduction

This section serves as an introduction to the study, outlining its context and background. This chapter also includes a synopsis of the study's theoretical framework, issue statement, goals, and research questions. This chapter also summarises the research methodologies, theoretical underpinnings, the study's significance and limits, and a plan for the remainder of the research.

1.2 Background of Study

Chatbots are conversational software that mimics human interaction via text or voice and are enabled by natural language processing (NLP) and artificial intelligence (AI) (e.g.Stoeffler et al., 2020, p. 217). According to projections by Weizenbaum (1966), chatbot use is expected to develop significantly over the next several years following the invention of the first chatbot in 1966 named Eliza.

Conversational agents, often known as chatbots, are currently being used in many scientific fields (Pham et al., 2018). Chatbots are already being utilized in multiple industries, including health, telecommunications, and banking (Ranoliya et al., 2017). Due to the digital transformation process, some public institutions are utilizing chatbots to provide new services or enhance existing ones. (Savin-Baden et al., 2015). There have been reports of chatbot usage in the education sector, such as in secondary schools and public universities (Shah et al., 2016). According to Chatterjee et al. (2020), there needs to be more research on this topic in an educational setting.

The Msizibot at UKZN is one example of a chatbot utilized in an educational setting. The Msizibot is an AI tool that assists students with online registration to provide an enabling environment that increases registration throughput. The Msizibot has also been enlisted to support academic activity via the learning management system (LMS) used for each academic year.

An LMS is a software system that lets its users (primarily educators and students) see, share, discuss, regulate, and track online learning activities, records, and more (Shah et al., 2016). One of the primary functions of an LMS is to allow teachers and students alike to access their online learning activities and monitor their progress.

A three-pronged interactive approach distinguishes the Msizibot from other chatbot services. The Msizibot enables the user to access a database of frequently asked questions (FAQs), engage the user in a conversational style of interaction that provides a comforting user experience and provides a conduit through which access to knowledgeable staff members may be obtained (Khelwa, 2022). One of the primary types of applications that chatbot technology is used for is to provide a frequently asked questions (FAQs) resource for users of websites (Troussas et al., 2017).

The chatbot is vital to UKZN's “service delivery” to current and prospective students. The UKZN chatbot can answer potential students' most sought queries by leveraging data from registration documentation and providing informed responses to students' questions. This will result in a higher quality of service to students compared to the alternative of waiting for some physical intervention by administrative personnel (Diachenko et al., 2019)

In February 2021, the chatbot was launched as a computer program that simulates human communication and provides predefined answers based on the words it receives in a chat interface. Due to the massification of higher education, the administrative burden has increased. Using artificial intelligence techniques to reduce human involvement requirement is one way to manage this cost effectively (Ho et al., 2018).

At UKZN, the Msizibot is a relatively new application. As a result, students may struggle to embrace and apply this new technology to improve their online registration and learning experience. The articles examined in this analysis show that chatbots have been used to further educational aims, including administration, advising, teaching and learning, research and development, and assessment (Ismail & Ade-Ibijola, 2019).

Several studies demonstrate that chatbots can provide accurate information to users and may be used to deliver course content and assist in the administration and registration of students through a digital platform (Chen et al., 2020; Nguyen et al., 2019).

Msizibot intends to use chatbots for administrative duties, making it easier for students to access vital information (Kavitha & Lohani, 2019). Chatbots provide students with learning materials, examinations, and quizzes to complete assessments, just like in classrooms (Ghazal et al., 2017).

Teachers can keep tabs on their students' development and expedite activities by sending the results of their examinations to them via chatbots. Students are increasingly relying on chatbots to assist them in choosing between various courses and extracurriculars (D’Silva et al., 2020;

Ho et al., 2018; Ismail & Ade-Ibijola, 2019). Several studies suggest that chatbot systems can help students with their research and growth by providing accurate answers to theoretical questions. A chatbot that directs students to relevant content on websites like Wikipedia might be helpful for students looking to expand their knowledge in their chosen area (D'Silva et al., 2020).

The current study covers the current state of chatbot usage at UKZN. While this technological intervention at UKZN is relatively new, it has not been widely promoted and its' usage is relatively low. Hence, this study addresses this problem by examining factors that may influence UKZN students intention to use the Msizibot at UKZN. The study will be introduced by providing a synopsis of the current literature on chatbot technology in general and its usage for online academic registration and learning systems.

1.3 Problem Statement

The field of higher education in South Africa has successfully implemented ICT to boost productivity and customer satisfaction. (Sandu & Gide, 2019). It has been demonstrated that research and development of chatbots can enhance education, communication, and production; aid teachers effectively; and reduce confusion.

Studies on AI applications in higher education have shown that there has been some progress in their utilization, with more people starting to take advantage of them. The importance of an intelligent assistant in higher education administration and student learning is highlighted by Hien et al. (2018), who envisaged that students will benefit most when pedagogical strategy is adjusted according to data generated by chatbots used in an academic setting.

Based on anecdotal evidence, online registration at UKZN was plagued by the system's inability to provide an instantaneous help feature that was context-driven and always available. Also, due to the Covid-19 pandemic, students and the UKZN academic community, in general, grew increasingly dependent on UKZN's LMS system for teaching and learning. While the university implemented many ad hoc interventions to assist users of the LMS, there was minimal interactive assistance available on an "on-demand" basis. These limitations of using online systems resulted in numerous delays and became the source of much frustration and pressure at UKZN. Online registration was plagued with multiple delays because of a lack of assistance in providing real-time help to the users. Also, one of the consequences of the shift to online learning is that the demand for quick access to educational resources will be greater. Within this context, the Msibot is being used to provide academic support.

There are various hurdles to adopting and accepting AI applications, some of which are technological. Still, most of these problems are related to behavioural issues centred on human aversion to embracing change, as Tarhini et al. (2015) outlined. This study aims to determine the potential challenges and benefits of integrating chatbot technology into higher education institutions for students' use.

1.4 Research Questions

Organizations have run their enterprises more effectively and efficiently because of technological advancements. This study aims to identify the factors that influence the acceptance of chatbot technology at UKZN, to improve online student registration and online learning.

The main research question is:

What is the behavioural intention of students at UKZN to use chatbot technology to enhance their online registration and learning experiences?

i. How do technology acceptance factors link to students' behavioural intention to use a chatbot to assist with online registration at UKZN?

ii. How do technology acceptance factors link to students' behavioural intention to use a chatbot to enhance their online learning experience?

iii. How can students' experiential knowledge of using the Msizibot (the current name given to the UKZN chatbot) for online registration be used to enable the adoption of chatbot technology for academic registration at UKZN?

iv. How can students' experiential knowledge of using the Msizibot to facilitate online learning be used to enable the adoption of chatbot technology to support online learning?

1.5 Research Objectives

Aim of the study:

The study aims to identify factors influencing students’ acceptance of the Msizibot at UKZN to support online registration and online learning. A concomitant outcome of the study is establishing factors contributing to students' greater usage/adoption of chatbot technology to support academic registration and online learning. The latter objective will be achieved by obtaining an insight into students' experiences of using the Msizibot at UKZN.

The specific objectives of the study (aligned to the study’s set of research questions) are listed as follows:

i. To determine students' **behavioural intention to use** a chatbot to assist with **online registration** at UKZN.

ii. To determine students' **behavioural intention** to use a chatbot to assist with **online learning** (at UKZN via the Learn2022 LMS).

iii. To leverage students' **experiential knowledge** of using the Msizibot at UKZN to provide support for online registration at UKZN, be used to identify factors that will contribute to greater adoption of chatbot technology to support academic online academic registration.

iv. To leverage students' **experiential knowledge** of using a chatbot for online learning to improve students' adoption of the Msizibot to facilitate online learning via the UKZN LMS.

1.6 Theoretical Framework

The study's research questions have been guided by the constructs of the UTAUT theoretical model. Ragheb et al. (2022) and Sandu and Gide (2019) surveyed the usage of chatbots at Indian colleges using the UTAUT model to learn more about what influences students' decisions to use this technology. Almahri et al. (2020) also used the UTAUT model to ascertain students' acceptance and adoption of chatbots in higher education institutions in the United Kingdom. It has also been used by Chatterjee et al. (2020), Zhou et al. (2020) and Akinnuwesi et al. (2022) in studies with a similar agenda.

The UTAUT theoretical model is predominantly aligned with quantitatively oriented research efforts (Rahi et al., 2019). Aligned with this observation, the study used quantitative techniques to drive the empirical phase of the study. The constructs from the UTAUT model were operationalized via closed-ended questions presented as a survey to the study's respondents. The study's quantitative empirical component was supplemented by a qualitative part that manifested as open-ended responses that captured students' experiences using the Msizibot at UKZN. The study's first two research questions were aligned with the quantitative component of the data collection instrument. The students' open-ended responses answered the third and fourth research questions, addressing their suggestions to enhance the chatbot's usability and performance. This study used the UTAUT framework to determine the factors for acceptance to support academic activity at UKZN.

1.7 Significance of Study

The relevance of this study is based on the value of contributing to the knowledge base of AI and chatbot technology in general. While the study has a higher education focus and provides knowledge from this perspective, it also includes knowledge on improving chatbot technology to provide better value to the user community. This study is also positioned within the 4th Industrial Revolution (4IR) technologies spectrum.

1.8 Dissertation Structure

An overview of the study's structure is provided as a "navigation tool" to convey the sequential ordering of the study's content. The study is structured as chapters 1 to 5, where each chapter has a focus on the following:

Chapter One: Introduction

The first chapter introduces the research topic and presents the central questions driving the current study considering the stated aims. References have been given regarding the study's delimitation.

Chapter Two: Literature Review

The second chapter is devoted to a review of the literature that is relevant to the study.

Chapter Three: Research Methodology

Chapter three provides the research technique, approach, and design. All relevant information has been provided and addressed, including the target population, sampling size and method, data collecting techniques, data quality control, and ethical considerations.

Chapter Four: Findings and discussions of results

This chapter covers provides details of the study's quantitative research findings. The quantitative data is presented in descriptive and inferential formats. The study's qualitative data are presented as textual transcript-based information.

Chapter Five: Conclusions and Recommendations

Chapter five discusses the findings and suggestions related to the study's goals. Also included are directions for future research.

1.9 Chapter One Summary

In Chapter One, the researcher established the study's research questions and objectives, and this section serves as a recap of that chapter. The primary purpose of this research was to identify the elements that affect UKZN students' acceptance of using the online registration and online learning tool - Msizibot. In this section, the researcher laid out the research problem, the study's aims, and the research's importance. Chapter 2 will look at the research that's been done on artificial intelligence in general and on people's attitudes regarding adopting chatbots.

Chapter 2 – Literature Review

2.1 Introduction

The introductory chapter's purpose was to summarise the overall topic and indicate the current study's general direction. The second chapter will assist in offering a background and theoretical framework for the evolution of the study's central themes.

The literature study defines vital concepts and theories, such as AI, and gives insight into the evolution of chatbots for usage/acceptance in education. These areas of study are crucial to the goals of the current study. This literature review aimed to determine whether chatbots have a place in higher education, whether they are helpful to students, and whether they can facilitate academic work at universities.

The goal is to amass relevant theoretical works to build solid research alongside the practical information gleaned from the study of the topic. AI has presented South African higher education with intriguing new prospects and challenges (D'Silva et al., 2020). Since its introduction, Opportunities to radically improve the effectiveness and efficiency of government have exploded with the advent of AI (Puaschunder, 2019). Artificial intelligence (AI) refers to computer systems that learn, synthesize, correct, and use data for complex tasks like humans (Savin-Baden et al., 2015). Students, faculty, administrators, and researchers in higher education stand to benefit significantly from AI, and as a result, this technology must be used (Battineni et al., 2020; Brown & Halpern, 2021). Thus, stakeholders must be encouraged to adopt AI, leading to overall advancements in South Africa's higher education system (Clarizia et al., 2018).

The governments of developed and developing countries are committed to improving education quality. AI and other cutting-edge technology can help attain this goal (Katchapakirin & Anutariya, 2018). Artificial intelligence (AI) would revolutionize how students are evaluated, gather information, etc.). All governments worldwide are increasing their investments in higher education to utilize current technology to broaden the scope of higher education (Dyachenko et al., 2017). Chatbots can improve education processes, including the ease of registration and e-learning at the college and university levels (Ragheb et al., 2022)

2.2 Advances in Higher Education within the 4IR Context

The increasing importance of incorporating the Fourth Industrial Revolution (4IR) into higher education teaching and learning is a growing concern worldwide. To meet the demands of the modern era, it is crucial for the education sector, especially higher education institutions

(HEIs), to embrace this digital technology trend. Moreover, the advancement of digital technology seeks to establish a shared corporate mindset within society and higher education (Ciechanowski et al., 2019). Consequently, it is projected that e-learning will eventually replace traditional classroom instruction in higher education (Yende & Yende, 2019). As digital technology continues to advance in higher education, physical instruction will inevitably be replaced by digital pedagogy. The utilization of digitalized testing has experienced a notable rise in higher education institutions (HEIs). Students now regularly rely on internet-connected laptops to stay engaged in school-related activities (Yende & Yende, 2019). Another valuable technique stemming from the Fourth Industrial Revolution (4IR) is hybrid learning, which significantly improves teaching and learning (Ganiyu et al., 2021). The implementation of these technologies fosters the advancement and progress of teaching and learning within higher education institutions.

2.2.1 Challenges of using 4IR tools in teaching and learning in HEIs

Teaching and learning in higher education institutions (HEIs) encounter various challenges when it comes to implementing Fourth Industrial Revolution (4IR) tools. Despite recognizing the benefits of 4IR technology in higher education, there is a need to revise the curriculum to align its content with technological trends. Penprase (2018) suggests that HEIs must adapt their curricula to incorporate technology systems for effective teaching and learning. While e-learning is considered a cutting-edge global system essential to higher education, it can pose challenges for institutions lacking in technology, particularly rural colleges (Butler-Adam, 2018). Addressing the needs of marginalized institutions is an integral part of the 4IR in higher education (Winanti et al., 2019). To successfully adopt digital technology and transition to the 4IR, relevant organizations such as the Department of Higher Education and Training, along with governmental organizations, should provide financial support to upgrade the infrastructure of rural-based institutions (Butler-Adam, 2018; Xing & Marwala, 2006).

Additionally, the lack of a digital culture, training, and knowledge hinders the progress of higher education teaching and learning (Hariharasudan & Kot, 2018). In order to address the rapid changes and complexities in employment, new frameworks should be developed for career and technical education (CTE) (Gleason, 2018). Within HEIs, the focus on technological possibilities often outweighs the consideration of educational benefits and impacts. The use of information and communication technology (ICT) in teaching and learning tends to prioritize technical capabilities rather than educational needs, presenting a challenge (Mbodila et al., 2013). Ramorola's (2013) findings revealed numerous difficulties in integrating 4IR tools into educational institutions. The study emphasized that the primary obstacles to efficient technology integration in educational institutions included a lack of technological policies, insufficient technology equipment, a shortage of competent personnel for technology integration and maintenance, and technical issues.

2.2.2 Opportunities for 4IR tools in HEIs

The incorporation of Fourth Industrial Revolution (4IR) tools in instructional activities within higher education institutions (HEIs) has created opportunities in the educational system. These tools have enabled better technological methods of knowledge dissemination. However, integrating technology requires adequate preparation, time, commitment, and financial resources (Ramorola, 2013). According to Schwab (2016), the 4IR plays a crucial role in enhancing higher education globally and promoting the development of essential skills such as e-learning, innovation, information and media technology, and life and job skills. These skills enhance individuals' competitiveness in the workplace and business. Furthermore, the advancement of digital technology has fundamentally transformed the world and markets, emphasizing the need for specific digital competencies (Gibbs, 2017).

Butler-Adam (2018) suggests that European schools, as well as American and Australian HEIs, have achieved success in their educational systems by embracing digital transformation. Serdyukov (2017) argues that nations that have adopted the 4IR in their higher education systems are better positioned to have a thriving economy in the future. Additionally, integrating 4IR tools into teaching and learning in HEIs benefits both students and teaching staff. Ultimately, as Penprase (2018) asserts, 4IR education equips students and faculty with the necessary skills to assume leadership roles in an ever-changing world, leading to their overall advancement.

2.2.3 Overcoming the challenges of the 4IR in advancing instruction in HEIs

Serdyukov's (2017) study reveals that efforts have been made in South Africa to align curricula with the required 4IR capabilities, with a particular focus on higher education. Collaboration between industry and the educational sector is essential to equip students with the necessary skills supported by digital technology, shaping the future of digital technology in higher education (Yende, 2021). To overcome the challenges posed by the 4IR in higher education, the curriculum should explicitly emphasize digital technology, including artificial intelligence (AI), automation, and internet technology, to ensure learners comprehend the concept of the 4IR and its practical applications in today's world.

The 4IR will profoundly transform the expectations and behaviours of teaching and learning within the classroom, mainly through the integration of digital resources in higher education (Butler-Adam, 2018). Analytical, creative, critical thinking, problem-solving, and digital literacy skills are essential for leveraging the opportunities presented by digital technology. However, these skills can only be effectively imparted to learners when instructors themselves possess the necessary technological knowledge (Yende, 2012). This emphasizes the importance of educators being technologically competent to bring the reality of the 4IR into the classroom. To prepare students for the opportunities presented by the 4IR, instructors in HEIs must acquire and demonstrate the requisite tools and abilities.

2.3 Nature of Artificial Intelligence

Computers are often considered the go-to when discussing artificial intelligence (AI). According to Chassignol et al. (2018), although computers provided the groundwork for the growth of AI, it is becoming increasingly evident that we should not consider the computer itself, its components, or its peripherals to be AI. Incorporating AI into physical objects like robots and smart buildings has been made possible by embedded computing, sensors, and other recent technological developments (Chassignol et al., 2018).

The definition and characterization of AI provided by Chassignol et al. (2018) comprise two facets. They identify AI as both a discipline and a body of thought. They define artificial intelligence as the branch of computer science concerned with replicating human intelligence in learning, problem-solving, pattern recognition, and adaptation (Chassignol et al., 2018). According to the work of Chassignol et al. (2018, p. 17), the field of artificial intelligence (AI) is "a theoretical framework for the development and use of computer systems with capabilities of human beings, in particular intelligence and the ability to perform tasks that require human intelligence, such as visual perception, speech recognition, decision making, and translation between languages". The preceding definition highlights similar components or properties of AI recognized by various scholars and in different studies. Artificial intelligence (AI) was defined by Sharma et al. as "devices that can approximate human reasoning" (Sharma et al., 2019, p. 1). Similarly to Pokrivčáková (2019, p. 138), artificial intelligence is a product of extensive research and development efforts that have brought together professionals from various fields such as system design, data science, product design, statistics, linguistics, cognitive science, psychology, and education. Pokrivčáková's definition and description focus on the educational sector, where AI has been developed to create intelligent education systems capable of performing diverse functions.

With the advent of AI in mobile devices, mobile education has advanced to a new level, allowing for more convenient, engaging, and individualized learning for students in less time. For instance, AI-powered chatbots can give individualized online education and transform teachers into chat partners. The student's grasp of the material can be gauged with this technological tool (Chen et al., 2020).

2.4 Education and Artificial Intelligence: The Technical Factors

Intelligent education, cutting-edge online learning, and predictive analytics all go under the umbrella term of "AI-enhanced education." Table 2.1 outlines the most common uses of AI in education and the technologies that enable them. AI-enabled education plays a more prominent role as learning demands increase (Rus et al., 2013). Educators and students can benefit from the timely and tailored feedback and guidance that intelligent education systems offer.

Table 2.1: Common uses for AI in education and AI-related methods (Rus et al.,2013)

Educational Scenarios for Artificial Intelligence	Artificial Intelligence related methods
Online and remote education	Virtual personalized assistants, Chatbots, Edge computing, real-time analysis
Tests administered to students	Academic analytics, a personalized learning strategy, and adaptive learning techniques
Essay and test scoring	Computer vision, image recognition, and prediction system
Smart school	Face and speech recognition, virtual laboratories, audio and video recognition, and sensing technologies
Personalized intelligent teaching	Learning analytics, data mining, and intelligent classroom systems

Artificial intelligence (AI) systems employ diverse techniques such as machine learning, data mining, and knowledge models to execute functions such as analysis, suggestion, comprehension, and acquisition of novel information. (Avella et al., 2016). Most AI education systems comprise intelligent technologies and system models (including learner, instructional, and knowledge models) (Kim et al., 2018).

2.5 The role of AI in Education

According to the research's literature review, AI has been used in schools for various purposes, such as streamlining administrative procedures, creating and delivering course materials, teaching, and assessing students' progress in their coursework. Utilizing software or web-based applications, Chen et al. (2020) argue that AI has facilitated the speed and accuracy of various administrative tasks, such as evaluating student work, grading, providing feedback on assignments, and streamlining the online registration process. Technologies such as chatbots, virtual reality, web-based platforms, robots, video conferencing, audio-visual files, and 3-D technologies have all been utilized to better the educational experience for students. The quality of the educational experience is enhanced for both instructors and students.

Further research into the available materials revealed that, with the help of AI, educational institutions might theoretically function beyond national and international boundaries. Using a web-based learning platform, students may study from anywhere in the world, using AI capabilities like language translation systems to personalize their education based on their unique strengths and limitations.

Administration, teaching, and learning systems that use technology to improve efficiency and effectiveness have been identified by Sharma et al. (2019). Pokrivčáková (2019) agreed, noting that intelligent systems with adaptable skills are the standard for AI in educational settings. AI in education is made possible by the concepts mentioned above and the properties of the systems, which allow it to do a wide range of tasks often performed by instructors while also improving students' learning experiences by coaching and adjusting instruction to each individual's needs and preferences (Pokrivčáková, 2019).

2.5.1 Artificial Intelligence in Education Administration

Administrative duties in education, such as reviewing student work, helping with registration, giving grades, and offering comments, have been singled out as a prime area where AI might significantly impact the future of education. As Sharma et al. (2019) stated, AI has improved the efficiency of institutional and administrative services in education, especially in distant and online learning. Some tools, like Learn2022/23, make it easier on teachers since they let them provide students feedback based on what they do on the platform. Positions similar to these can be found in other research and publications that propose methods to facilitate administrative duties. Intelligent tutoring systems (ITSs), as suggested by Rus et al. (2013), among other things, grade and provide feedback on student work (Rus et al., 2013). Teachers who collaborate with ITS can better focus on their primary duties—giving direction and teaching children to succeed academically—while also gaining time for administrative activities. The arguments and findings by Mikropoulos and Natsis (2011) supplement those in previous research; leveraging and using AI in education has increased effectiveness and efficiency in performing administrative activities, such as assisting with registration and helping with students' assignments. Software like Turnitin, which grades student work and checks for plagiarism, is already commonplace in the modern online classroom environment, allowing teachers to handle various administrative responsibilities. AI has reduced the time spent on administrative activities that previously fell on teachers' or educational administrators' shoulders (Chen et al., 2020).

2.5.2 Artificial Intelligence in Learning

The study also encompasses learning, a crucial feature of education. Articles were evaluated and analyzed to determine how AI has been accepted, deployed, or leveraged to improve students' education. Moreover, many applications and software using AI to enhance students' educational experiences were singled out. Customizing and personalizing curriculum and information per the learner's requirements, abilities, and capabilities (Mikropoulos & Natsis, 2011) is one significant way AI has enhanced students' learning. The cornerstone of learning is information, and some methods make acquiring that information more enjoyable and engaging or experiential for the students (Mikropoulos & Natsis, 2011; Wartman & Combs, 2018). From a different angle, the use of AI in education has made it possible for people worldwide to access the same educational resources via the Internet (Mikropoulos & Natsis, 2011; Sharma et al., 2019). The learning experience can be enhanced by using a platform that allows for individualising content, increasing the likelihood that information will be absorbed and retained.

Pokrivčáková (2019) further noted that AI integration and chatbot-use enhance students' learning experiences by using machine learning algorithms to tailor content to each individual's skill level and interests (Chen et al., 2020). Artificial intelligence (AI) can be used to tailor lessons and resources to each student (Pokrivčáková, 2019).

2.6 Self-service Technology

Users' interactions with companies that don't offer human support are evolving due to self-service technology interfaces like chatbots (Davenport et al., 2020). Changes like this are also occurring in developing nations like South Africa. In a survey conducted by Ernst & Young in South Africa, almost all business owners said they expected to have a positive impact on their bottom line from implementing AI tools like chatbots. Specifically, the optimization of chatbots as a safe and effective means of communicating with clients has been affected by the coronavirus (COVID-19) pandemic (Lubbe & Ngoma, 2021).

SST (self-service technologies) features, like SnapScan, have been developed by financial institutions to enable easy payments and other services, such as facial recognition, fingerprint scanning, and voice communication with chatbots (Siderska, 2020). However, chatbot applications are still in their infancy, even if they are being deployed in the context of emerging markets (Huang et al., 2021). Chatbots have the potential to enhance consumers' experiences greatly, yet, only a remarkable technical encounter would motivate people to adopt and employ new SST such as chatbots. (Åkesson & Edvardsson, 2018).

2.7 Chatbot Technology

A chatbot uses artificial intelligence to communicate with users by answering their queries and giving feedback (Clarizia et al., 2018, pp. 291-302). It is a software system that processes and analyzes human speech that intends to provide digital gadgets with the capability of emulating human behaviour. A computer program designed to instantly answer user questions (Rosruen & Samanchuen, 2018, pp. 1-5).

Since Alan Turing's 1950 proposal of the Turing Test (which asked, "Can machines think?"), the concept of a chatbot has been growing in popularity (Turing, 2009, pp. 23-65). The original chatbot, Eliza (Weizenbaum, 1983), was designed to mimic a psychotherapist by conveying user input to them in the form of questions. Based on the user's query, it provided a response utilizing pattern-matching algorithms and a template-based response system (Brandtzaeg & Følstad, 2017, pp. 277-392). The system's fundamental operations were defined with the help of Artificial Intelligence Markup Language (AIML) and pattern-matching (Marietto et al., 2013; Molnár & Szüts, 2018). Chatbots like SmarterChild, Alexa (Amazon), Siri (Apple), Watson (IBM), Assistant (Google) and Cortana (Microsoft) have appeared in recent years as a direct result of technological progress (Reis et al., 2018). Since 2016, chatbot research and development has exploded, leading to numerous chatbot systems with practical applications across industries (Adamopoulou & Moussiades, 2020).

Artificial intelligence (AI)-powered technology, especially chatbot systems, has opened up many new possibilities for many industries (Dsouza et al., 2019). Chatbots have found a home in the education domain, where they serve dual purposes: helping pupils hone their social skills while simultaneously giving teachers a helping hand through the introduction of automation (Dsouza et al., 2019). Chatbots are becoming increasingly popular in education because of their benefits in terms of increased connectivity, streamlined workflow, and diminished room for error in student-teacher exchanges (Ondáš et al., 2019). Today's educational institutions require a targeted, individualized, and outcome-based online learning environment, and these tools make it possible (Cunningham-Nelson et al., 2019, pp. 299-303). More so, Chatbots are amoral and dependent agents who control imaginary dialogues (Murtarelli et al., 2021).

2.8 General Chatbot Structure

Many communities and organizations have proposed chatbot frameworks (e.g. Wit.ai – Facebook, Microsoft Bot Framework – Microsoft) (Dale, 2016; Del Sole, 2018; Mitrevski, 2018). Different conversation kinds, data structures, training procedures, and programming environments form the basis of each framework (Hien et al., 2018). Although their designs vary, they aim to receive user messages actively and efficiently and provide answers.

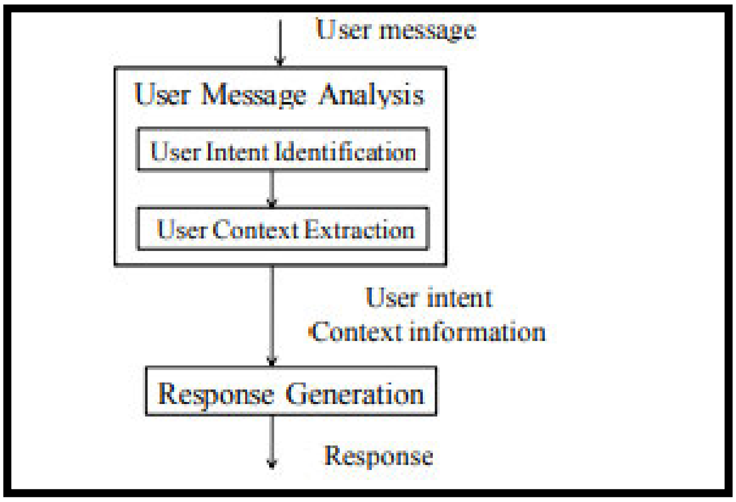

Figure 2.1: The structure of a general chatbot (Hien et al., 2018)

The basic layout of a chatbot is shown in Figure 2.1. Components such as these, which analyze user messages and generate responses, make up a chatbot in its most basic form.

User message analysis uses natural language processing (NLP) strategies to decipher user conversation.

There are two primary components:

- *Identifying User Intent*: This effort aims to identify user intent by analyzing user-provided text. It can be seen as the message's goal.
- *Extracting User Context*: Information about the user's context is derived from the message following the user's intent.

These variables can include everything from the user's clickstreams with the chatbot to the user's profile to the time of day to the user's actual location as determined by GPS data. Chatbots use that information to deduce the user's intent and respond appropriately.

The *User message analysis* subsystem provides the **Response generating subsystem** with information about the user's intent and context, which is used to construct responses to the user. Pattern-based model (Joshi et al., 2015), the Retrieval-based model (Wu et al., 2016), and the Generative model (Patidar et al., 2017) are the three models utilized to generate the correct answers. In the Pattern-based paradigm, chatbots generate responses by comparing incoming user messages against a database of predefined question-and-answer patterns. The Pattern-based paradigm is rigid, while the Retrieval-based model is adaptable. In particular, this paradigm uses APIs to query and analyze data in a sales database, such as a product's price.

Regarding producing replies based on recent and historical user messages, the Generative model stands head and shoulders above the other two. However, numerous challenges are involved in its construction and instruction (Hien et al., 2018). This means that it requires extensive training data to get satisfactory conversation results. This limitation is a significant reason why this technique has not been widely employed to create a chatbot.

2.9 Pedagogical roles

Three distinct educational responsibilities, including facilitating learning, providing assistance, and mentoring, were identified during the literature review.

Chatbots are employed in the *Learning* function as a pedagogical tool to impart knowledge and skills that include regular conversational exercises contextualised to the academic curriculum is one method of achieving this goal (Fryer et al., 2020). Another option is to supplement classroom instruction with extra resources, such as voice assistants for use in the home for recreational purposes (Bao, 2019). These include chatbots that pretend to be your pen friend in another country (Kim, 2019). This chatbot encourages students to use a dictionary, check their grammar, and improve their fluency in the target language through natural conversation.

When functioning in an aiding capacity (*Assisting*), chatbot behaviours can be summed up as making the student's life easier by relieving the student of some or all of their responsibilities. Making data more accessible is one way to do this (Sugondo & Bahana, 2020), while automating routine tasks is another (Suwannatee & Suwanyangyuen, 2019). The chatbot in (Sandoval, 2018) illustrates this tool because it provides generic responses to questions concerning a course, such as its exam schedule or office hours.

The chatbot takes action in the *Mentoring* role and focuses on the mentee's growth. The student receiving this type of assistance is the focal point of the conversation. It should be prompted to engage in meta-cognitive activities like planning, reflecting, or evaluating his performance.

The chatbot, for instance, encourages students to reflect on their learning experiences to build transferable abilities (Cabales, 2019).

2.9.1 Domains for educational chatbots

The study's author singled out specific uses for chatbots in educational contexts. These can be classified into three broad groups based on their educational function: learning chatbots, helper chatbots, and mentor chatbots.

Learning chatbots

There are seven subcategories within the larger topic of Learning Chatbots, which is concerned with chatbots that take on the pedagogical role of Learning. Seven categories are listed: 1) Learning a Language, 2) Learning to Code, 3) Learning Communication Skills, 4) Learning About Educational Technologies, 5) Learning About Cultural Heritage, 6) Learning About Laws, and 7) Learning Math. More than half of all articles in this field deal with using chatbots to aid with language learning. It is standard practice to employ them as virtual conversation partners for language learning and training. Bao (2019) seeks to alleviate the stress associated with learning a new language by simulating human conversation in that language via a chatbot.

Assisting chatbots

There are four distinct subcategories within the larger topic area of Assisting Chatbots, which is concerned with chatbots that take on the pedagogical role of Assisting. Here are the four types of support offered: 1) administrative aid, 2) campus support, 3) course help, and 4) library support. In Administrative Assistance, chatbots that aid in navigating institutional bureaucracy by offering 24/7 support are the most often studied and published type of AI. This is explained by (Galko et al., 2018), where a chatbot replaces traditional student enrolment forms.

Mentoring chatbots

Chatbots that take on the educational role of Mentoring fall under the Mentoring Chatbots category, further broken into the following three categories. To begin with, there are three ways to use chatbots: 1) to inform, 2) to recommend, and 3) to serve as a scaffold for other bots. The CRI(S) chatbot is an example of a Scaffolding Chatbot; it promotes beneficial ideas and tricks to the learner through conversation, scaffolding the development of life skills like self-awareness and conflict resolution (Gabrielli et al., 2020).

2.10 Chatbots in the Educational System

Many educational chatbots have already been in use. Chatbots can be used for pedagogical or operational purposes (Arsovski et al., 2019); chatbots for online registration are considered functional, even when used in an educational context. Administrative duties like student advising and assistance are handled by chatbots that are not programmed to provide pedagogical value (Bii et al., 2018). Chatbots developed explicitly with an educational objective are known as educational chatbots (Bii & Too, 2016).

The research on how chatbots might benefit the education sector is expanding. Academics have widely utilized chatbot technology. A survey of the relevant literature shows that chatbots have been used in many pedagogical situations, from teaching and learning to administration and assessment to advisory services and even research and development (Cho, 2016; Kamal et al., 2020; Smutny & Schreiberova, 2020).

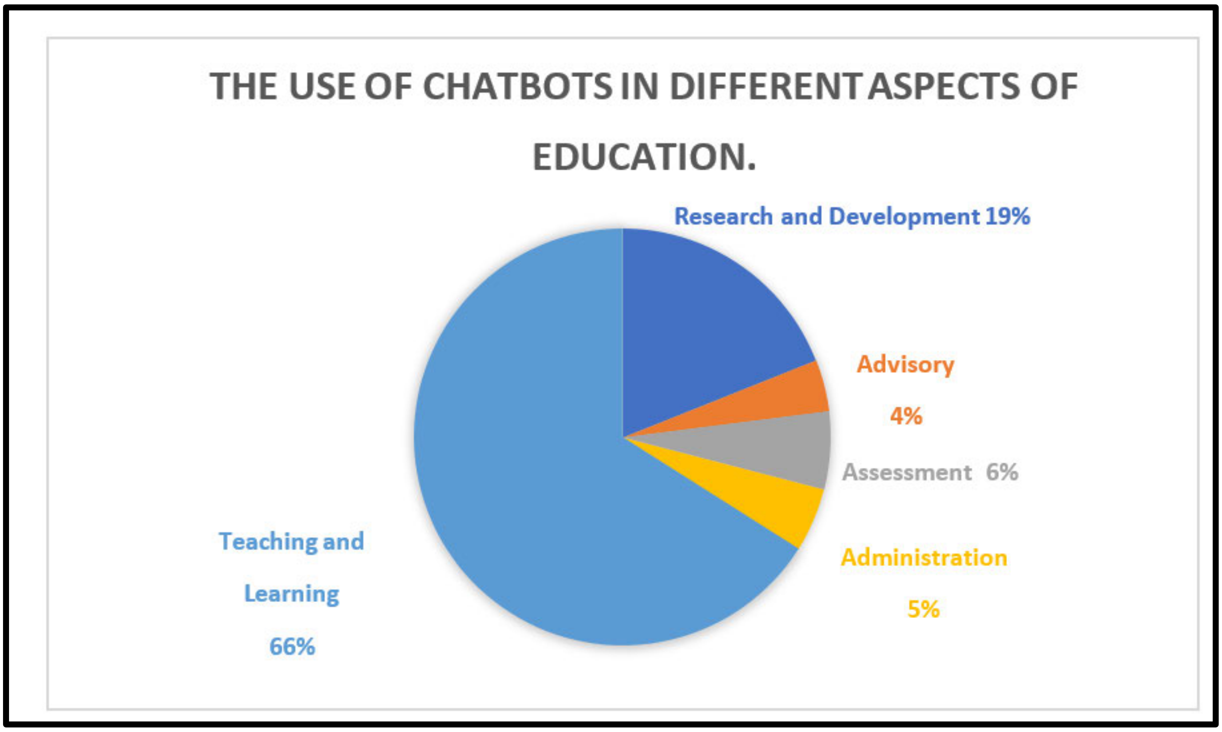

Figure 2.2: The Use of Chatbots in Different Aspects of Education (Arsovski et al., 2019)

Figure 2.2 indicates the percentage of scholarly articles that focused on varying aspects of education, such as teaching and learning (66%), research and development (19%), assessment (6%), administration (5%), and advisory (4%).

As the review shows, chatbots are widely employed in **Teaching and Learning**. Chatbots can be used to teach students in online environments (Nguyen et al., 2019). Chatbots are used in teaching and learning to facilitate interaction between teachers and pupils (Ho et al., 2018). Bots can facilitate student-to-bot communication, providing generic and individualized support services (Bii et al., 2018; Song et al., 2017). Chatbots adapt to each student's needs and make online education more convenient and accessible. According to Sandu and Gide (2019), AI is essential for educational development. A chatbot can anticipate students' needs and personalize their learning experience through conversational AI (Crockett et al., 2017). Chatbots have been shown to boost students' academic performance, knowledge retention, and knowledge acquisition (Troussas et al., 2017).

Universities and colleges can use chatbots to enhance their services, develop novel ideas, and cut labour costs. Research by Elnozahy et al. (2019) examined the effectiveness of a chatbot in assisting with new student enrollment, advising current students, and fostering long-term relationships. AI chatbots improve classroom instruction and school administration (Lee et al., 2019). Chen et al. (2020) suggest that chatbots could provide feedback and grades for student work. Conversational interfaces aid students with questions about enrollment, financial aid, and course costs (Hwang et al., 2020).

Assessment: chatbots enabled by AI can analyze and evaluate academic progress. Chatbots assess students' knowledge by collecting their responses to questions. Chatbots can be used to access study materials, tests, and quizzes (Elnozahy et al., 2019)

Exam results from chatbots allow teachers to keep tabs on students' development and move lessons along more quickly (Ho et al., 2018).

Advisory: The use of chatbot technology for advising conversations is another significant area of application in education. In this review, chatbots can be seen being utilized to guide students in making important decisions about their academic programs and endeavours (D'Silva et al., 2020; Ho et al., 2018; Ismail & Ade-Ibijola, 2019) created a chatbot to help people learn more about themselves and current employment trends so that they can make more informed choices regarding their education and professional development.

Several studies have shown that chatbots can help students with **Research and Development** by responding to academic study-related chats. Chatbot technology is used for postgraduate research recommendations. Ureta and Rivera (2018) developed a chatbot to instruct students in the methods of STEM study (Mckie & Narayan, 2019; Ureta & Rivera, 2018). The research also uncovered a chatbot that could guide students in gathering knowledge from various sources like Wikipedia and teaching students from different backgrounds to develop in-depth practical experience in their respective industries (Paschoal et al., 2018, pp. 839–848)

Research in educational institutions has shown that chatbots can perform administrative activities (Hong et al., 2008; Lee et al., 2019), but further research is needed to confirm this (Ranoliya et al., 2017).

2.11 Chatbot usage in South Africa

Developing nations like South Africa require innovation to generate a workforce capable of competing globally and construct education systems of a high standard (Sandu et al., 2017). South Africa has become a leading player in the worldwide chatbot market due to its widespread adoption across various industries. Chatbots are increasingly employed in the financial sector to manage consumer inquiries (and frequently asked questions) and provide advice on bank services and products (Das et al., 2017). Chatbots are being used to assist clients in the insurance industry with tasks such as submitting claims, acquiring policies, determining the status of their policies, and locating providers, their branches, and other service providers (Gentsch, 2018). In transportation, chatbots provide real-time details regarding taxi rides, booking and verifying flights, and analysing traffic (Dan et al., 2019; Graham & Dobruszkes, 2019). Chatbots have been put to use in the field of e-commerce to handle consumer questions and complaints, as well as to track orders, make payments, and monitor order status (Fleming et al., 2018).

2.12 Chatbots in Higher Education

Recent years have burdened our nation's universities heavily due to the rising demand for education. The increasing ratio of students to teachers is evidence of this (Ketakee & Champaneria, 2017). In other words, less time and resources will be devoted by teachers to helping each student (Patidar et al., 2017). Because of this, many students could not learn effectively and eventually left school (Hone & El Said, 2016; Patidar et al., 2017). Numerous proposed solutions have been proposed, but most can't be executed due to a lack of resources and insufficient infrastructure (Oeste et al., 2015).

To help with these massive problems, scientists and management have begun providing chatbots for the educational industry. Using a chatbot to address today's academic challenges sounds promising. Educators will heavily use chatbots (Pham et al., 2018). Chatbots' ability to provide personalized, in-depth assistance to students is a significant benefit (Winkler & Söllner, 2018). Useful in traditional classroom settings and MOOCs (massive open online courses) where students are enrolled in the hundreds or thousands. In higher education, a chatbot can be trained from a broad number of sources, including both actual classroom instruction and supplemental materials.

2.13 Chatbot platforms

Most studies have focused on creating web-based chatbots. The online chatbots were developed for several informational functions. In this vein, KEMTbot (Ondáš et al., 2019) is a chatbot system that details the department's employees and where they work. Some chatbots, like Oscar (Latham et al., 2011), are used as intelligent tutoring systems to teach students about computer science. In addition, other web-based chatbots like EnglishBot (Ruan et al., 2019) assist students in learning a new language.

Some articles included mobile-only instructional chatbots (e.g., phone, tablet). These articles appeared in periodicals in early 2019 and 2020. Mobile chatbots serve several functions—case in point: Rexy registration aid (Benedetto et al., 2019). The fields of the chatbots in the selected articles were courses, displaying exam results, and providing comments. The E-Java Chatbot is another example of a programming language-teaching chatbot. Other articles discussed chatbots designed for desktop use and their many applications (Daud et al., 2020). A chatbot developed by Redondo-Hernández and Pérez-Marín (2011) considered students' individuality and learning preferences. Most desktop-based chatbots date back to before 2013, most likely because modern consumers find desktop-based systems too inconvenient to use because they need to download, install, update, and depend on a specific operating system. Unsurprisingly, most chatbots were hosted on the web, most likely because web-based programs do not need to be downloaded, installed, or updated, and so work regardless of the user's computer's operating system (Kuhail et al., 2022). More and more people are using chatbots that are accessible via mobile devices. The rising use of mobile applications is likely to blame for this trend.

2.14 Determinants and challenges to the adoption of chatbots for academic activity

Education is undergoing radical shifts due to the widespread adoption of chatbot technology. A recent study found that using chatbots in education increased test scores and student engagement (Winkler & Söllner, 2018). Several studies have shown that chatbots can be successfully applied in educational contexts (Durall & Kapros, 2020, pp. 13-24; Hien et al., 2018; Ho et al., 2018; Kumar et al., 2016; Mikropoulos & Natsis, 2011; Murtarelli et al., 2021; Ndukwe et al., 2019; Okonkwo & Ade-Ibijola, 2020). The educational system may gain from using these chatbots in several ways.

Content Integration: Teachers and professors can now integrate content by uploading all course materials to a shared online repository accessible only to registered users.

Included are topics to be covered and a schedule for tests, quizzes, homework help, and other related activities. Personalization of student data is a strength of chatbots. Students can be informed of upcoming extracurricular activities, workshops, and other events of interest. According to the review's findings, chatbots can be used in higher education to give students 24/7/365 access to relevant course materials (Akcora et al., 2018, pp. 14-19; Wu et al., 2020; Yang & Zhou, 2011; Yang & Evans, 2019).

Rapid Access: According to the reviewed literature, one of the advantages of chatbots is that it facilitates immediate access to educational content (Wu et al., 2020). Save time and improves student learning and performance by providing quick and simple access to relevant information (Clarizia et al., 2018; Ranoliya et al., 2017).

Engagement and Motivation: Students' motivation and interest in online education are crucial in today's digital world. Instead of reading textbooks or course materials, they'd use their smartphones to surf the web and read articles.

Reviewed articles show that interactive systems like chatbots keep students interested and involved in their studies (Chen et al., 2020; Pham et al., 2018; Troussas et al., 2017).

Students are not bored when learning with a conversational agent and can learn at their own pace. In this way, chatbots can help improve student involvement in education (Adamopoulou & Moussiades, 2020; Allam et al., 2020; Molnár & Szüts, 2018).

Accommodating Multiple Users: The ability to adapt to many users simultaneously was identified as another significant benefit of utilizing chatbots in educational settings by reviewing the chosen publications. This means several students in different locations can use the same chatbot simultaneously to get the necessary answers. One of the main advantages of a chatbot for educational purposes is that it can be used by many people simultaneously, as Wu et al. (2020) noted. In agreement, Rooein (2019) argued that a chatbot could answer a user's questions in parallel, freeing up their time to focus on other matters.

Instant assistance: One of the primary benefits of implementing chatbots in the classroom is the ability to provide immediate assistance to students. Educators and students can get instant feedback on their questions and assignments with the help of chatbots (Al Badi et al., 2022). Chatbots were found to be adaptive to learners' actions and emotions (Graesser, 2016), provide immediate support during individual learning (Okonkwo & Ade-Ibijola, 2020) and help students automate activities like submitting homework and responding to emails (Molnár & Szüts, 2018).

Challenges

Chatbots are increasingly being used in education, expanding their purview to encompass all areas of education. Staff and students at educational institutions could benefit from the technology's ability to deliver customized services at lightning speed (Terblanche & Kidd, 2022). Some difficulties arise, however, with the widespread implementation and use of chatbots in education. Ethical, insufficient evaluation, user attitude, programming, and data integration issues are just some of the obstacles to implementing chatbot technology in education, as reported by the reviewed literature (Chatterjee et al., 2020; Cunningham-Nelson et al., 2019; Paschoal et al., 2018; Ruan et al., 2019).

Ethical concerns: Chatbots are a form of artificial intelligence that has quietly crept into people's daily lives, raising ethical concerns. Chatbots allow people to have automatic conversations using only natural language. Thus, there are moral questions about implementing chatbots, especially in education. Some ethical concerns with using a conversational agent have been brought to light by Ruan et al. (2019), including many perspectives, lack of transparency, invasion of privacy, and the agent's persona. While developing a chatbot, the authors argued that developers should avoid relying solely on abstract ideas and instead use a contextual and plural approach, considering the application domain and the intended audience. It is the responsibility of the user to choose the purpose of the chatbot and the methods by which they will engage with it. To prevent betraying the user's confidence, agents must be aware of the user's expectations. To win over users, a chatbot system must maintain a consistent identity (Huang et al., 2021). Privacy concerns led people to wonder where all this information would be stored. As chatbot systems spread throughout society, including education, protecting users' personal information is more critical than ever. Thus, it is crucial to understand the chatbot's context regarding privacy when seeking to comply with regulatory standards or established privacy rules. Agent persona is affected by gender, age, race/ethnicity, culture, and socioeconomic status.

It is crucial to review whether the agent persona's design and accompanying dialogues encourage potentially dangerous behaviour and evaluate its impact on the connections users might desire to develop with the agent. Usability, privacy, and security are all examples of ethical concerns that may influence people's decisions to use new technologies (D'Silva et al., 2020; Shumanov & Johnson, 2021).

Evaluation issue: According to Rapp et al. (2021), judging a chatbot's design is not enough based on how well it works or how satisfied or engaged its users are. This is consistent with the reasoning and observations made by Paschoal et al. (2018, pp. 389-348), who stated that most studies undertaken to test the efficacy of chatbot systems used a tiny and negligible sampling population. Song et al. (2017) suggested empirical research demonstrating that students can improve their learning outcomes by interacting with a chatbot system in a digital classroom setting. An adequate method for assessing the efficiency of a software engineering product and a more extensive and statistically significant sample population should be employed to test the efficacy of chatbot systems.

User attitude: The user attitude was identified by reviewing the selected papers as another hurdle to using chatbot systems in education. Chatterjee et al. (2020) found that people's perceptions of using artificial intelligence in higher education affect their intent to implement AI. Equally convincing was evidence from another study of software engineering product adoption demonstrating how user mindset affects the uptake of new software instruments (Okonkwo & Ade-Ibijola, 2020). Therefore, it follows that it would be suitable for those in charge of tertiary education to influence stakeholders' perspectives to alter those groups' actions (Chatterjee & Bhattacharjee, 2020). Students will resist adopting and using chatbot technology in education if they have an unfavourable impression of its potential uses in educational settings—people who like what they see will be more likely to use the new technology.

Chatbot programming issues: One of the most challenging aspects of creating a chatbot is the coding involved (Pham et al., 2018). NLP is used in the making of a chatbot. NLP is a field of computer science that helps computers understand, analyze, and interpret human language. The problem is, how exactly should a chatbot be taught to respond appropriately? Users may ask the same thing in various ways, and you must be prepared to respond. "What time is it?" or "Could you please check the time?" The chatbot system may deliver a reliable response to the first question but make mistakes when responding to the second. Grosz (2018) argues that some of the most important concerns related to the use of NLP and computational linguistics concern the possibility of dialogue system failure, the effect of social chatbots on human communication, and poor system performance. As a dialogue system, a chatbot must comprehend what is being said and anticipate its users' social and emotional requirements

(Cunningham-Nelson et al., 2019, pp. 299-306; Huang et al., 2021). A well-programmed chatbot system will be able to teach itself to respond appropriately to users' inquiries.

Maintenance and supervision: Based on the findings, it is clear that there is a need for careful oversight and upkeep as chatbots are developed and introduced into educational contexts. Having a human oversee the chatbot's functioning helps guarantee that the information it receives and gives out is accurate and that it is being used as intended. Maintenance checks the chatbot's functionality and ensures the data bank is current. The bot's output quality depends on the information it receives (Cunningham-Nelson et al., 2019, pp. 299-306). The user believes the chatbot will always give them the correct replies, which hinges on having valid input data. In addition, the bot's database should be updated regularly so the chatbot can consistently deliver up-to-date and correct information. Including new data is a complex process. Before adding something new to the knowledge bank, be sure it hasn't previously been added. There's the small matter of how adding new data can affect the usability of existing data searches. The longer it takes for the bot to complete an investigation, the more information it has to sift through. Sometimes, the exact keyword will appear in several databases (Okonkwo & Ade-Ibijola, 2020). The search method for a specific phrase only returns some data from the broader data sets; occasionally, the most important one is absent. It can be challenging to build a chatbot system since it requires constant attention.

2.15 Theoretical Framework

Venkatesh et al.'s (2003) Unified Theory of Acceptance and Use of Technology (UTAUT) will guide research in this area. The UTAUT model was created to study users' acceptance and intention to use new technology. The two leading (most significant) components of this model are the constructs of performance expectancy (PE) and effort expectancy (EE), both of which emanate from the Technology Acceptance Model (Davis, 1989). To provide a more robust technology acceptance model, the constructs of Social Influence (SI) and facilitating condition (FC) were added by Venkatesh et al. (2003).

The Technology Acceptance Model, sometimes known as TAM, is the most commonly used model to describe how users react to new forms of technology (Shah et al., 2016). The technology acceptance model (TAM) is one of the most popular models for researching the acceptance of information systems (Snyder, 2019). According to this model, system use (actual behaviour) is determined by perceived usefulness (PU) and perceived ease of use (PEOU), both of which are related to an attitude toward use that, in turn, is related to intention and finally to behaviour (Smutny & Schreiberova, 2020).

The Theory of Planned Behavior, also known as TPB, has long provided helpful conceptual frameworks for coping with the intricacies of human social behaviour (Semiz & Semiz, 2021). The model's primary purpose is to characterize the external factors affecting the users' internal attitudes and use intents and anticipate the system's acceptance and use. In other words, the model attempts to predict the approval and usage of the plan (Zawacki-Richter et al., 2019).

Researchers chose UTAUT because it is comprehensive and was created using six models. These are TAM, TPB, TAM+TPB (combined TAM+TPB), the PC utilization model; innovation diffusion theory; and social cognitive theory (Bigham et al., 2008). Including the additional constructs has rendered UTAUT more predictive than any of its contributing individual models (Alrawashdeh et al., 2012). Efiloğlu Kurt and Tingöy (2017) found that behavioural intention and use behaviour in e-learning vary by nation and that all UTAUT model constructs apply to e-learning. There are more than nine different models for technology adoption; the UTAUT model was chosen since it combines the behavioural intention of adoption and technology use (Alshehri et al., 2012). Since it concentrates on the two main factors (acceptance and service), the UTAUT model can evaluate the adoption and use of technology in higher education institutions (Venkatesh et al., 2012).

2.15.1 UTAUT Adopted in Previous Research

Researchers in various fields have used UTAUT in multiple contexts to measure the propensity for adopting and using new technologies. Venkatesh et al. (2003) encouraged researchers to examine the topic and test the hypothesis in various contexts. Applications include people getting used to the idea of social robots, people using mobile devices more frequently, virtual classrooms being used to aid in education, learning management systems, artificial intelligence (AI) and the internet of things, mobile commerce, and mobile banking (Wu et al., 2012).

There have been several studies conducted on the topic of chatbot adoption recently. The adoption and spread of chatbots in the German insurance industry were investigated using a mixed-method approach, as Rodríguez Cardona et al. (2019) reported. Practitioners and potential customers said they prefer human help to a chatbot when making complex insurance selections, indicating that "relative benefits" and "IS infrastructure" were the most crucial adoption factors. Kuberkar and Singhal (2020) used a modified version of the UTAUT (n = 463) to investigate what makes individuals comfortable using an AI-powered chatbot for public transit in a Smart City. Performance expectancy, effort expectancy, social influence, facilitating conditions, and behavioural intention all play a significant role in whether or not a person intends to utilize a chatbot.

The UTAUT model, since its inception, has been applied and tested extensively for predicting system usage and making decisions related to technology adoption and technology usage in a wide range of fields, including interactive whiteboards and chatbots in an educational setting (Umak and Orgo, 2016; Umak et al., 2017), near-field communication technology and virtual assistants (Khalilzadeh et al., 2017), mobile health and health chatbots (Hoque and Sorwar, 2017), home telehealth services (Chauhan and Jaiswal, 2016). There has been a significant amount of research on the UTAUT framework. This framework provides a structure for understanding the rationale and practice of utilizing IT and ISs. The UTAUT model significantly contributes to the technology adoption and usage study because of its capacity to combine many TAMs (Venkatesh et al., 2003).

The impact of using a chatbot to enhance banking services was also studied by Kim et al. (2019) using the UTAUT model. This study found a significant relationship between the desire to utilize a chatbot and factors such as performance expectancy, effort expectancy, social influence, and trust in information and security.

Despite its wide-ranging applications, it is evident that UTAUT is a valid theory for investigating how chatbots, and other technologies, affect user adoption behaviour. Because of the chatbot service's infancy, the researcher also explored the possibility of using the UTAUT2 model. In the UTAUT2 model, constructs such as value for money, habit, and hedonic appeal were considered viable constructs to underpin the study. However, the lack of user experience in using chatbot technology led to concerns that users would not be able to answer questions about habits and pricing at this early stage. Based on a literature review on chatbot adoption, the researcher has used the UTAUT model to underpin the current study. The researcher has inferred that the constructs central to UTAUT will provide an ideal context to answer the study’s research questions. While there is a dearth of literature on chatbot adoption in the higher education sector, there is sufficient congruency with this topic regarding how it has been studied in other contexts. The prominent role of technology acceptance constructs to guide studies on chatbot technology acceptance has been a crucial factor in the decision to opt for a quantitative, UTAUT-oriented strategy to inform the current study’s methodology in the context of the higher education sector, specifically UKZN.

2.15.2 Performance Expectancy (PE)

PE is "the degree to which an individual believes that using the system will help him or her attain gains in job performance". Previous research has elicited that PE significantly predicts behavioural intention (Venkatesh et al., 2003). The concept of performance expectancy is similar to and equivalent to perceived usefulness, outcome expectancy, and relative advantage. Zhou et al. (2010) found that PE, social influence, and facilitating conditions affect user adoption. Doan (2020) verified that a customer's performance expectancy substantially impacted their propensity to make an online transaction in Vietnam using chatbots. As a result, students' PE about how well chatbots function influences whether or not they will use these technologies to access academic activities.

2.15.3 Effort Expectancy

EE is "the degree of easiness connected with using the system". Many studies have revealed that EE and its latent variable are significant and can be used to predict whether or not a user will accept new technology. The concept of EE is embodied in different models, such as ease of use and complexity (Venkatesh et al., 2003). The theory behind the other models shows that a person's attitude toward technology adoption can be predicted by their perception of ease of use (EE), which is quite similar to EE in principle (Allam et al., 2020). EE was found to substantially affect individuals' behavioural intentions to employ chatbots in the banking sectors in Ugandan banks (Catherine et al., 2017). Thus, students' willingness to use chatbots is correlated with their EE of how much effort they will need to put in.

2.15.4 Social Influence

A person's perception of the importance others attach to them when it comes to the new system is known as "social influence" (SI) (Venkatesh et al., 2003). Several studies have shown that SI impacts whether or not people intend to utilize a particular piece of technology (Hien et al., 2018). Social influence substantially affected an individual's inclination to use chatbots in Ugandan banks that required fingerprint verification (Catherine et al., 2017). Doan (2020) demonstrated the importance of SI in influencing a Vietnamese consumer's online purchase propensity. As a result, the likelihood that a student will utilize a chatbot to improve academic activity is correlated with their level of social influence.

2.15.5 Facilitating Conditions

It's a measure of how much a person believes that the necessary technological and supporting infrastructure is in place to allow for the use of a new system (Venkatesh et al., 2003). The facilitating conditions construct, as outlined by the UTAUT framework, is associated with the "use behavior" dependent construct rather than "behavioral intention." As a result, the study excluded the consideration of FC since its primary focus was solely on investigating Behavioral Intention (BI).

2.15.6 Behavioural Intention

Using technology with the belief that it will help one accomplish their objectives more quickly is referred to as Behavioral Intention (BI) (Ajzen, 1991). Predictors of actual behaviour are accurately predicted by this Behavioural Intention (BI) (Zawacki-Richter et al., 2019). In this case, BI serves as a mediating variable, affecting behaviour and favouring the action toward which one has expressed an intention (Bassam Nassuora, 2013). This study applied this concept to evaluate students' openness to adopting and making greater use of chatbot applications.

The theoretical model that will be used in the study is illustrated in Figure 2.3.
The illustration in Figure 2.3 reflects an adapted version of the UTAUT model where the primary UTAUT constructs have been slightly modified to reflect the outcomes required for the current study.

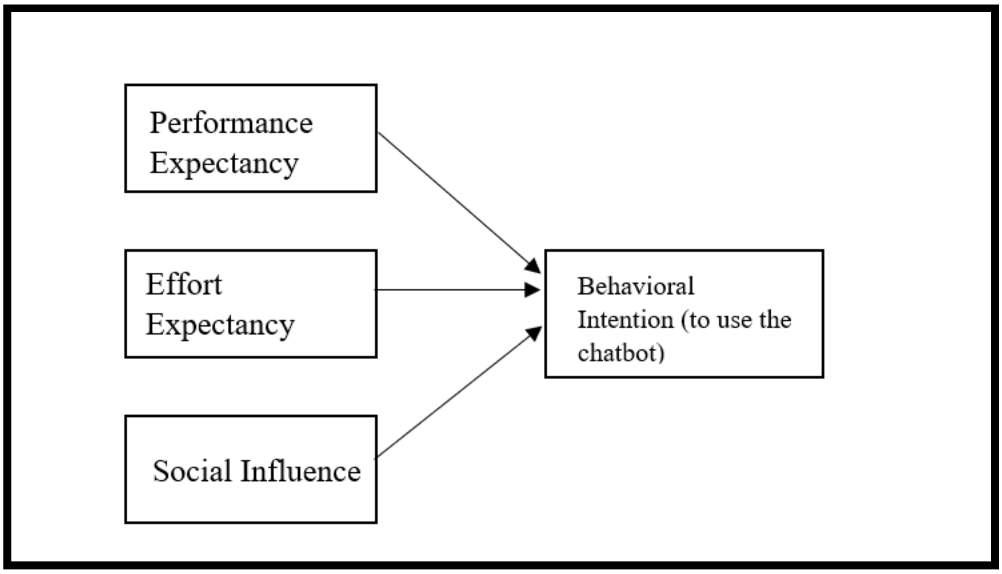

Figure 2.3: The Study's theoretical Model adapted from the UTAUT Model (Venkatesh et al., 2003)

2.15.7 UTAUT Modification

The researcher has also decided to remove the presence of the moderating variables typically found in the UTAUT model; this is not unwarranted because such a strategy has been used in previous studies (e.g. Jairak, 2009; Nassuora, 2012; Thomas et al., 2013), Gender, experience, voluntariness and age were all deleted from the suggested study models. However, from a more pragmatic perspective, the researcher has also observed that the influence of each of the moderating variables can be mitigated via the following explanation: From the standpoint of the voluntariness construct, it should be noted that in most higher education settings, chatbot usage is optional for students. Hence, voluntariness does not qualify to be a variable in the study. A similar argument is invoked for the construct of age because the range of ages for the student population in higher education settings is minimal, suggesting that there is only a marginal difference in the ages of respondents to the study. The omission of gender and experience levels could be seen as a delimitation of the study because the researcher has consciously decided to focus the study's outcome on extrinsic variables that influence technology adoption

Facilitating Conditions (FC) play a crucial role in shaping the foundation of the study. Although the current study did not directly measure use behavior, the researcher adapted the Unified Theory of Acceptance and Use of Technology (UTAUT) model to investigate the potential relationship between FC and Behavioral Intention (BI). FC serves as a fundamental dimension that allows us to evaluate the extent to which various conditions, such as accessibility, resources, and support, facilitate or hinder users in their adoption of the technology. By exploring the interrelationship between FC and BI, the researcher aimed to gain insights into how these facilitating conditions contribute to users' willingness to embrace and utilize the technology. The facilitating conditions construct, as outlined by the UTAUT framework, is associated with the "use behavior" dependent construct rather than "behavioral intention." As a result, the study excluded the consideration of FC since its primary focus was solely on investigating Behavioral Intention (BI).

This decision is not a unique one and has been observed from previous studies that used the UTAUT model to study technology adoption (e.g.Arenas Gaitán et al., 2015; Marchewka et al., 2007; Semiz & Semiz, 2021; Thomas et al., 2013)

2.16 Chapter summary

The literature concerning the adoption of artificial intelligence chatbots and their various uses has been evaluated in this chapter. Chatbots in higher education can be deployed for multiple purposes, including learning, administrative duties and motivation, and self-service provision.

In addition to discussing the advantages and disadvantages of using chatbots in higher education, this chapter has examined the various factors that could encourage or discourage their widespread implementation. Also, a variety of different theories and frameworks for the adoption of technology were investigated. The research methodology utilized in this study will be discussed in the following chapter.

Chapter 3 – Research Methodology

3.1 Introduction

Research methodology refers to the set of procedures or guidelines used to carry out a particular piece of research in accordance with the ideas, beliefs, and values that guide that approach (Somekh et al., 2005, p. 346). The methodology used to address the research objectives and questions is described in this chapter. The different parts that make up the research methodology are discussed in this chapter.

The table provided below illustrates the correlation among the research questions, research objectives, the constructs within the UTAUT framework, and the specific analytical techniques employed for each research question.

Research Question	Research Objective	UTAUT constructs	Analysis
How do technology acceptance factors link to students' behavioural intention to use a chatbot to assist with online registration at UKZN?	To determine students' **behavioural intention to use** a chatbot to assist with **online registration** at UKZN.	• Performance Expectancy • Effort Expectancy • Social Influence • Behavioral Intention	Quantitative
How do technology acceptance factors link to students' behavioural intention to use a chatbot to enhance their online learning experience?	To determine students' **behavioural intention** to use a chatbot to assist with **online learning** (at UKZN via the Learn2022 LMS).	• Performance Expectancy • Effort Expectancy • Social Influence • Behavioral Intention	Quantitative
How can students' experiential knowledge of using the Msizibot (the current name given	To leverage students' **experiential knowledge** of using the Msizibot at UKZN	• Performance Expectancy • Effort	Thematic

to the UKZN chatbot) for online registration be used to enable the adoption of chatbot technology for academic registration at UKZN?	to provide support for online registration at UKZN, be used to identify factors that will contribute to greater adoption of chatbot technology to support academic online academic registration.	Expectancy • Behavioral Intention	
How can students' experiential knowledge of using the Msizibot to facilitate online learning be used to enable the adoption of chatbot technology to support online learning?	To leverage students' **experiential knowledge** of using a chatbot for online learning to improve students' adoption of the Msizibot to facilitate online learning via the UKZN LMS.	• Performance Expectancy • Effort Expectancy • Behavioral Intention	Thematic

Table 3.1: Correlation among Research questions and objectives, UTAUT constructs and analysis

3.2 Nature of study

A study design specifies the steps that need to be taken by the researcher to produce the desired findings. There are two main research design approaches, as outlined by Aljowaidi (2015).

According to Merriam and Tisdell (2016), a research design comprises a time-based strategy based on the research question. It serves as a guide for identifying sources and types of information and a set of systematic actions to complete the study. Merriam and Tisdell (2016) called it a "framework" that describes the interconnections between the study's variables and every research process step. Schwaferts (2015) describes a research design as a "simple explanation of how you plan to answer your research questions and draw your findings."

According to Creswell (2002), research design may be seen as a blueprint for data gathering, from selecting a topic to deciding on a methodology to determining how to interpret the results.

The methodology is the blueprint for conducting research. It consists of preconceived notions and philosophical beliefs that inform how the study questions are framed and the procedures used. Dissertations and theses rely heavily on the reliability of the research methodology that guides the selection of methods, instruments, and theoretical framework.
Saunders et al. (1998)'s theoretical concept of a "research onion" (Figure 3.1) provides one foundation for the building of research methodologies (2016). The research onion depicts the several layers or steps that must be completed to get at a workable methodology and can be seen as a very tiring portrayal of the work involved (Raithatha, 2017).

From the research logic to the research design — the primary techniques and procedures of data collecting and analysis — one must first outline the study's central philosophy, select appropriate methodologies, methods, and strategies, and establish a timeline (Figure 3.1).

The research onion consists of six levels: research philosophy, deduction, choice of methodology, strategy, time Horizons, and techniques and procedures. Research philosophy focuses on a study's ontology, epistemology, and axiology. Deduction involves testing the hypothesis by observing and collecting data. The choice of methodology is whether to use quantitative or qualitative methods. Strategies include experiments, surveys, archival research, case studies, ethnography, action research, grounded theory, and narrative inquiry. Time Horizons involve collecting data in a cross-sectional survey or longitudinal study. Techniques and procedures involve selecting sample groups, creating questionnaire material, and preparing interviews.

The research onion framework (Saunders et al., 2019) is used in this chapter to demonstrate the study's process.

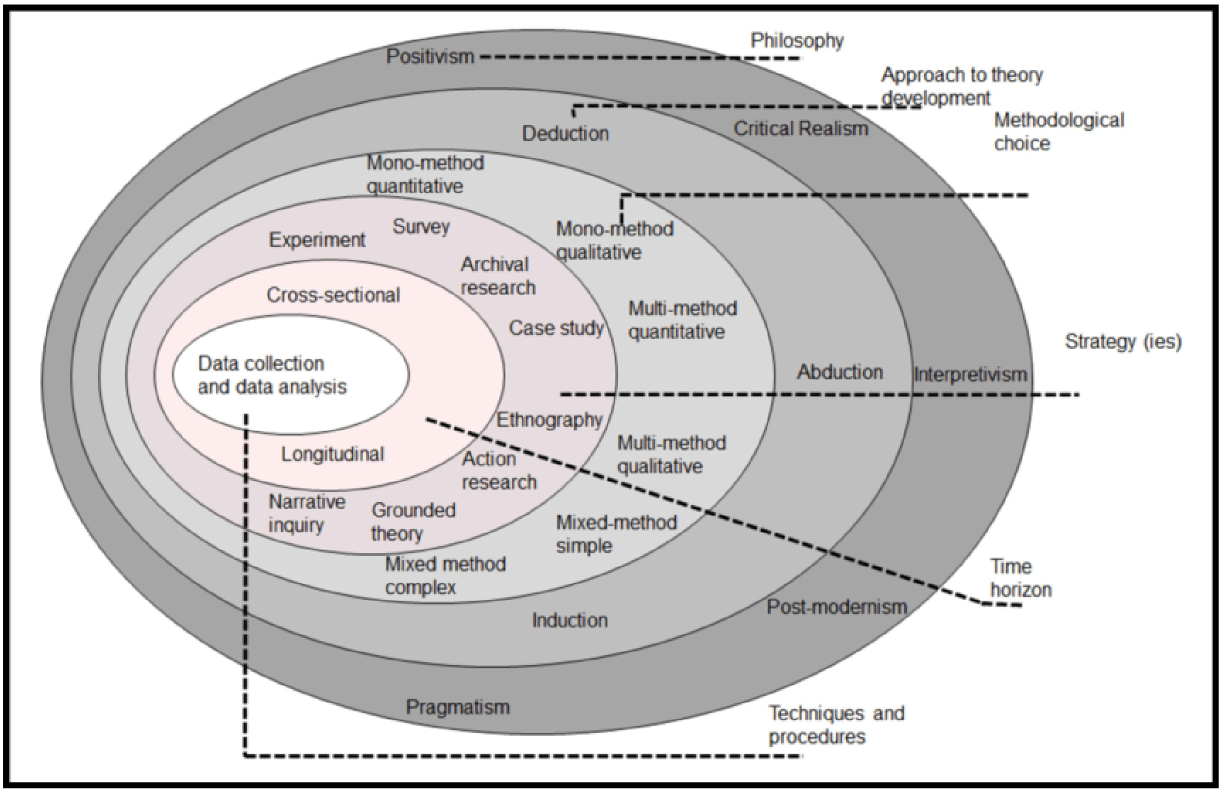

Figure 3.1: Research Onion Framework (Saunders et al., 2019)

3.3 Research Philosophy

The first layer of the research onion model is the research philosophy, also known as the research paradigm. The definition of a paradigm offered by Khan (2014, p. 214) is that it is "a collection of values and practices which is shared by members of a scientific community, which function as a road map, outlining the issues that researchers should be focusing on and the explanations that will be accepted. The primary research philosophies are positivism, realism, interpretivism, and pragmatism (Saunders et al., 2007, p. 138).

Positivism seeks to verify and account for empirical data, while realism relies on introspection and analysis. Interpretivism tries to understand people's personalities, social interactions, and cultural backgrounds. Pragmatism is an approach to evaluating beliefs or theories by their practical applications. According to Saunders (2016), if the study difficulties do not imply that one particular form of knowledge or method should be embraced, this strengthens the pragmatist's perspective that working with many types of knowledge and techniques is entirely viable.

In this study, the inclusion of qualitative research methods aligns with the pragmatic philosophy guiding the research approach. Pragmatism emphasizes practicality and problem-solving, which is crucial when addressing questions related to enhancing the user experience and optimizing the chatbot's functionality. While the positivist approach provides valuable quantifiable data, pragmatism recognizes the importance of open-ended feedback from users (Khan, 2014). Qualitative research complements the quantitative analysis by providing a deeper understanding of user motivations, attitudes, and contextual factors (Saunders, 2016), allowing us to identify practical insights and improvements that may not be apparent through quantitative means alone. In essence, the pragmatic use of qualitative research enriches the study's comprehensiveness and empowers us to offer actionable recommendations for improving the user experience.

The present study embraces a positivist research methodology due to its quantitative nature.

3.4 Research Approach

The research strategy is the plan of action that will lead to the discovery of meaningful answers to the research questions (Saunders, 2012). Depending on the specifics of the study, one can use several alternative approaches. Using the research onion, you can choose from seven methods, including experiments, surveys, case studies, action studies, grounded theories, ethnographies, and archival research, as Saunders et al. (2007).

The two primary research strategies are the deductive and inductive approaches.

The deductive approach requires studies to start with an existing theory from which hypotheses or questions can be derived and tested (Saunders, 2016). Research using a deductive approach may need a rewrite of the theory and new rounds of hypothesis testing if its findings force such changes. In contrast to the deductive method, the inductive approach uses the study's results to develop a theory (Schwaferts, 2015). Researchers often use the inductive method when prior studies are absent.

The research strategy adopted for the current study is guided by the researcher's philosophical disposition that resonates with positivism and pragmatism. The study is centred on the UTAUT theoretical model, ensuring a strong alignment with the deductive logic that guided the study. The principal methodology adopted for UTAUT studies is a quantitative, survey-driven approach. The description of the study as being quantitative is informed by the assertion that quantitative research uses numerical data to probe causal relationships and is analyzed with statistical tools and visual representations (Saunders et al., 2016). To get a generalised view that accurately provides knowledge of the elements that influence the adoption of the Msizibot by students at UKZN, the researcher opted for a deductive, quantitative approach where the constructs of the UTAUT model operationalise human behaviour towards technology. The study also used a descriptive research approach since its goal was to provide a broad context to enhance the discussion about the relationships between the study’s main variables. However, in observance of the philosophy of pragmatism, where it is recognised that no single strategy provides an optimal opportunity to understand a phenomenon, the researcher has opted to bring in an element of qualitative research by supplementing the data collection instrument with two open-ended questions. This strategy will allow the respondents to express their experiences of using the Msizibot in a non-prescriptive manner. This will also provide the researcher with a deeper insight into students’ perceptions of the Msizibot technology, thereby providing empirical evidence on how the technology could be improved.

3.5 Research Methods

A methodological decision is the third layer of the research onion process (Saunders, 2016). Any research project can use either quantitative, qualitative or a combination of the two (M. Saunders et al., 2009). When a study has clear hypotheses or aims and intends to draw broad findings, it will likely take a quantitative method (Alshamaila, 2013). Qualitative research methods are employed if a thorough topic investigation is desired. The researcher's preconceptions about the studied phenomenon will determine the method used.

There are three different research methods: qualitative, quantitative, and mixed. Qualitative research aims to uncover people's perceptions of their everyday surroundings. Quantitative research involves measuring the variables of a data sample and using statistical methods like means, correlations, and frequency analysis to conclude the connection between the variables. Mixed research involves quantitative and qualitative methodologies to get a deeper meaning of a phenomenon. The benefits of each method are combined in the mixed-method process, and the drawbacks of using a single approach are mitigated when multiple procedures are employed.

3.6 Research Strategy

The term "research strategy" encompasses the methodologies employed by researchers when addressing their research inquiries (Saunders & Tosey, 2013). In the realm of research, various strategies are employed, including experimental, survey, case study, action, grounded, ethnography, and archival research approaches.

Experimental research strategy is primarily utilized when assessing the impact of a phenomenon on two distinct groups: a controlled group and a treatment group (Saunders &

Tosey, 2013). Case study research strategy entails selecting a specific subject with particular characteristics for in-depth analysis (Saunders & Tosey, 2013). Action research is commonly chosen when attempting to identify solutions to identified problems (Creswell & Poth, 2017). Ethnography research involves conducting investigations within the context of a specific culture or group, while archival research relies on existing data sources, often utilizing secondary data (Creswell & Poth, 2017).

A survey strategy allows researchers to collect data from respondents, which serves as a representative sample of the entire population, facilitating objectivity (Alvesson & Sköldberg, 2017). In essence, the "survey strategy presents the opinions of a population by studying a sample of that population" (Creswell & Poth, 2017). Typically, a survey strategy involves the use of questionnaires to gather data from a subset of the population. It aligns with the deductive approach (Jagdale et al., 2018).

In the present study, a survey research strategy was employed because a sample was drawn from a portion of the university student population to investigate the factors influencing the Msizibot usage.

3.7 Time Horizon

The time horizon in research pertains to the duration for data collection. As outlined by Saunders and Tosey (2013), there exist two distinct types of time horizons: cross-sectional and longitudinal.

Longitudinal time horizon research entails the accumulation of data over an extended period, making it suitable for experimental and archival research methods (Kim et al., 2017). Conversely, cross-sectional time horizon research involves the collection of data within a brief timeframe, typically gathered only once for the study's purposes (Saunders and Tosey, 2013). Cross-sectional research studies are most appropriate for investigations utilizing case study and survey research strategies.

In the present study, the cross-sectional time-horizon approach was adopted because it aligns with a survey research strategy, and data collection occurred over a short duration.

3.8 Data Analysis and Data Collection

In the research "onion," the techniques and methods layer specifies the processes used to gather and analyze the data. The data collection for the current study will be discussed in this section as the plans for data analysis.

3.8.1 Research Instrument design

One of the essential parts of any research is creating suitable instruments to test hypotheses. A research instrument's plan must be carefully considered to collect and quantify its target construct. This study's research instrument consisted mainly of closed-ended questions guided by the UTAUT model. The researcher added two open-ended questions to elicit data regarding participants' familiarity with and usage of the Msizibot in online learning and registration. The open-ended questions were optional and required a response if the study's participant had previous chatbot technology experience (including the Msizibot). (See Appendix 3 for the questionnaire).

Sarantakos (1998) claims that the questionnaire's design decides whether or not responders can complete all questions. The questionnaire's design should be user-friendly and include a time estimate for completion. According to Edwards (2002), a more extensive questionnaire has a negative impact on the response rate. Long qualitative questions in a questionnaire may also discourage people from answering it. Creating a credible and trustworthy survey for participants to fill out is crucial if one wants their responses to provide light on particular research questions and aims. To do this, the study followed the six processes outlined in Figure 3.2, to develop their questionnaire, as Saunders et al. (2009) suggested.

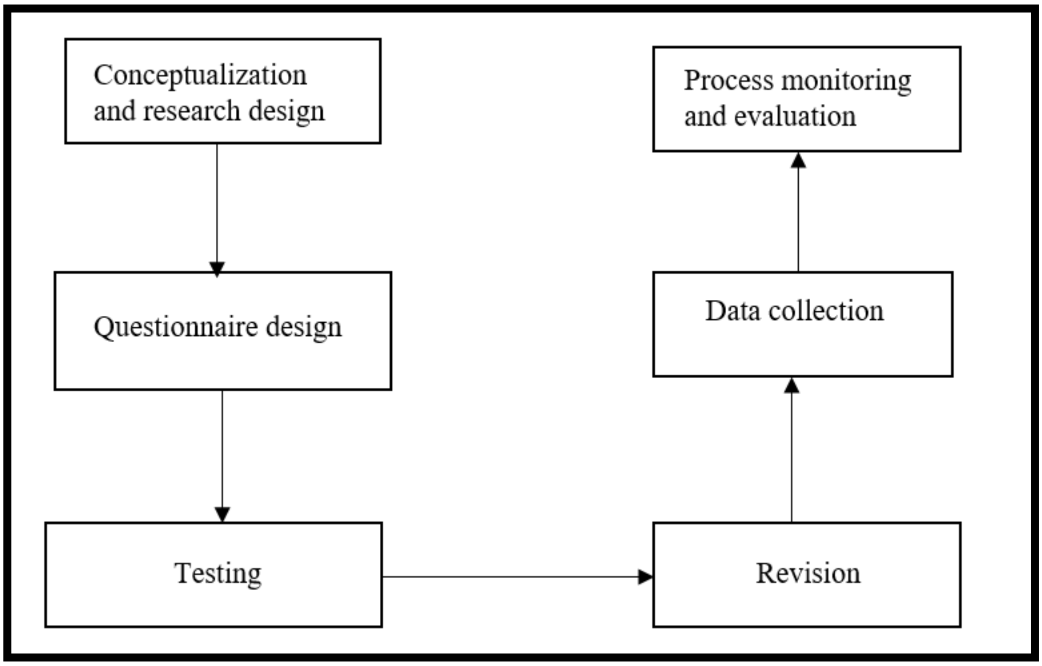

Figure 3.2: Questionnaire design process (Saunders, 2009)

3.6.1.1 Conceptualization

Schouten et al. (2021) described that research instrument conceptualisation requires developing a list of measurable variables. The quantifiable variables must address the research questions. The relevant context can't be captured without valid and dependable variables. In this study, questionnaire questions were framed regarding the constructs from the UTAUT framework. Furthermore, the questionnaire's questions were adapted from previous research.

3.6.1.2 Questionnaire construction process

According to Phellas et al. (2011), questionnaires are an inexpensive and reliable way to collect vast data. The questionnaire utilized in this study is based on the standard UTAUT questionnaire (Venkatesh, 2003) and has been modified for this study's purposes (see Appendix 3). Detailed descriptions of the questionnaire's sections follow.

Section A: Demographic information - This section aimed to gather basic participant demographics. Participants were asked to provide demographic information such as age, gender, degree and computer experience.

Measurements

Section B: Questions were asked to test the UTAUT paradigm's foundation.

The questions were presented in a 5-point Likert scale format, elucidated in Table 3.2.

Scale	Score Points
Strongly Agree	1
Agree	2
Neutral	3
Disagree	4
Strongly Disagree	5

Table 3.2: The 5-point Likert Scale Format

Questionnaire Design

There were 24 questions across all questionnaire sections, which took approximately 15 to 20 minutes to complete. This study employed a formally organized survey questionnaire to obtain information from participants. Ross (Ross, 2005, p. 3) defines a structured questionnaire as one "in which each responder is exposed to the same questions and method for classifying replies." Furthermore, Hair (2007) claimed that every researcher should develop a questionnaire that may reduce bias in the study as much as possible by paying attention to the three fundamental principles of questionnaire design: questionnaire language, the planning of the questionnaire structure (grouping of research variable, scale, and coding), and the questionnaire's presentation. The study's questionnaire was carefully crafted with the three aforementioned considerations. As a result, the questionnaire was split into two parts so that students may provide different responses for the two distinct aspects influencing the University's academic activities: online learning and online registration.

The questionnaire had both short-answer and open-ended questions. In addition, a five-point Likert scale was used for closed-ended questions to make responses more quantifiable during analysis and to generate a more organized questionnaire. As a result, an open-ended question was included and strategically positioned after the survey to collect information that respondents might not have felt comfortable sharing in answer to the survey's more conventional, closed-ended questions.

Technology Adoption

This section was used to elicit knowledge of respondents' experience of using Msizibot and their behavioural intention of continued usage of the technology. Table 3.3 indicates the questionnaire structure designed to accommodate the primary UTAUT constructs.

UTAUT Constructs	Number of question items

Performance Expectancy	4
Effort Expectancy	4
Social Influence	3
Behavioural Intention	2

Table 3.3: The UTAUT Constructs and Corresponding Questionnaire Items

Section C - A hermeneutic phenomenological study is based on the events and experiences of selected participants during a historical event (Creswell, 2002; Creswell & Poth, 2016); thus, the researcher has provided a section of the questionnaire that consisted of 2 open-ended questions about students' experiences of using the chatbot. Open-ended questions offer options to ask inquisitive questions that seek a more resounding answer that may be unique to the respondent (Creswell, 2013; Haq, 2015). When doing a study with an element of qualitative research, the reliability of both data and results is paramount. The idea is to build rapport, encourage personal sharing, and facilitate memory (Bogdan et al., 2011; Merriam & Tisdell, 2016).

An essential part of this hermeneutic phenomenological study is developing open-ended questionnaires directly related to the research issues. The researcher is attempting to explore the participants' perspectives on the Msizibot based on their experience of using the technology. As Creswell (2012, pg. 222) notes, open-ended questions are justified because they enable respondents to "better describe their experiences unrestricted by any perspective of the researcher or prior research findings and allows the participant to create the potential responses." The surveys were pre-tested to prevent any misconceptions.

Open-ended questions were asked, and students were allowed to share their thoughts on their Msizibot experiences. The two questions focused on the chatbot's ease of use and suggestions for possible enhancements to the technology. The ease of use question was based on respondents’ experiences using the technology, and the second will focus on enhancing the chatbot's effectiveness and performance.

3.6.1.3 Testing

Errors in the questionnaire might be found and fixed during the testing phase. The researcher can perform informal testing by reviewing the questionnaire for typos and evaluating the clarity of the questions. When conducting formal tests, a supervisor or experienced researcher ensures that all questions are uniform and error-free (Saunders, 2012). In addition to ensuring that participants understand the questions, the pilot study can help check for mistakes. During this stage, it is also determined whether the questionnaire questions effectively measure the target variables (Alshamaila, 2013).

3.6.1.4 Pilot Study

Errors in the instrument can be found during a pilot test, making it an essential aspect of the research process. For this investigation, 10 participants (UKZN students) were randomly selected for a pilot test.

Indications from the pre-test include:

- Despite their busy schedules, the researcher had to convince some respondents to complete the surveys.
- More than 30 minutes were needed to finish the questionnaire, which was too long. Hence, closed questions, in particular, may not have elicited the full range of responses;
- Many were reluctant to share their thoughts on the Msizbot's ease of use.

The pilot survey allowed for the refinement of the questionnaire and the modification of any problematic items to ensure that respondents faced no difficulties completing the survey. Evaluation of the validity of the questionnaire and the dependability of the data to be collected was made possible by pilot testing.

A statistical expert was handed the questionnaire to check for any remaining errors. All of the statistician's recommendations were implemented. Three people were asked to fill out the questionnaire for this study. A professor in Information Technology reviewed the survey, applying established standards for completeness and consistency, and noted that the study should be divided into two parts: one for online learning and another for online registration. Secondly, a doctoral candidate in Statistics was requested to provide informed feedback on ordering the questions so that it could be presented as a coherent document that enabled easy statistical coding and analysis. To obtain a view from a typical respondent to the study, a student at the university was also asked to fill out the questionnaire. After receiving feedback from these three people, the revised questionnaire was produced and distributed to the respondents. Finally, a Master's level student with knowledge of UTAUT assessed the questionnaire to ensure that the questions were consistent with the theory underpinning this research.

3.6.1.6 Data collection

Collecting information can be done either personally or via electronic or postal means. Hand-delivered, email, postal service, web-based, and over-the-phone surveys are just a few examples of the many methods available for gathering information (Alshamaila, 2013). Online questionnaires were used to compile the data for this research. Since the survey was administered online, participants were under no time constraints. To reach as many students as possible in UKZN quickly and affordably, this study used Google Forms-based electronic questionnaires to disseminate through various social media platforms, including WhatsApp.

Additionally, a notice was posted on the official UKZN Noticeboard with a clear message seeking participation in this survey from members of the UKZN community who have used the Msizibot for registration or online learning through Moodle/Learn 2022. None of the participants received any payment or bonus for participating. They were informed they could withdraw from the study if they felt uneasy.

3.9 Target population

A research's population consists of all the individuals, events, and other phenomena that spark the investigator's interest. For people who fit a specific profile, the researcher has established part of the study's intended group (Draugalis & Plaza, 2009).

Only students from the Pietermaritzburg and Westville campuses at the University of KwaZulu-Natal were included in the sample. Those enrolled at UKZN and actively using the Msizibot on the university's website were considered for inclusion[1] in the study. According to UKZN (2016), an estimated 22,160 students from the Westville and Pietermaritzburg campuses use the university's online resources; hence this will serve as a proxy for the whole student body. The current research will make use of a purposive sampling strategy. Finding students who have utilized Msizibot is essential for a reliable study. Students who have used Msizibot are better prepared to respond to survey questions than those who have not.

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[1] The invitation to request participation clearly stated that students who have an experience in using the Msizibot should participate

3.10 Sampling strategy

A sample is a subset of a larger population from which data will be drawn (McCombes, 2019). The size of a sample is determined by the population being studied. Most researchers know how many people to expect in a study's population (McCombes, 2019). For the current study, the sample size was determined using statistical theory, and 378 participants were suggested, as Sekaran and Bougie (2016) recommended. With a confidence level of 95 percent to 99 percent and a margin of error of 1 percent to 5 percent, this sample size selection ensures that the results will be accurate. Three hundred eighty surveys were sent to the study's sample population, but only 232 complete surveys were returned for analysis. The Pietermaritzburg campus had 154 respondents, while the Westville campus had 78. A 61 percent response rate is acceptable (Dillman, 2011; Fincham, 2008)

Technically, the study’s population would consist of all Msizibot users (potential users) at the Pietermaritzburg and Westville campuses of UKZN. This will basically entail all students who are registered for academic study at both these campuses. According to Sekaran and Bougie (2016, p. 247), this exploratory study is suitable for purposive sampling as the method of choice for this study. The process of purposive sampling, called judgment sampling, involves making a conscious decision to select a participant based on the attributes the participant possesses. It is a method that is not random and does not require any underlying hypotheses or a predetermined number of participants.

To put it another way, the researcher chooses the necessary information and then searches for individuals who can supply it. They are also eager to do so due to their level of expertise or previous experience. To ensure accurate results, rather than selecting students at random, the researcher sought out those who have used Msizibot in the past. These students are better prepared to answer survey questions regarding the Msizibot than those who have not. Purposive sampling is based on the concept that students with a specific amount of chatbot experience will be better equipped to assist in the research.

The researcher collected quantitative replies through purposeful sampling, improving insights and producing more detailed research findings (Song et al., 2017). The researcher eliminated responses that weren't relevant to the current study.

3.11 Data analysis

The frequency distribution was analyzed using descriptive and inferential statistics in this study. Google Forms distributed the surveys via the UKZN Notice system and social media. All replies were successfully collected using Google Forms. This allowed the researcher to download the data in Excel format easily. Transferring the data from Excel to Statistical Software for the Social Sciences (SPSS) v25 allowed for in-depth statistical analysis. SPSS was used for the quantitative analysis. The information was catalogued and fed into the SPSS program for statistical analysis. Descriptive statistics, cross-tabulation, and statistical relationship analysis were all used to make sense of the quantitative data. Participants' completed questionnaires were analyzed by adding their responses to several questions. Both a spreadsheet program and SPSS were used to analyze the data. The frequency distribution graphs determined the mean scores, variances, and standard deviations from the respondents' data. According to Nielsen (1993), collecting user feedback through surveys is a great way to learn about many usability elements.

Two open-ended questions were devised to probe users' impressions of the chatbot's functionality and ease of use. Thematic analysis was applied to the open-ended questions to identify reoccurring patterns or trends. The researcher learnt more about the data by reading the responses. Information was recorded and coded using NVIVO software and sorted into coherent themes and subthemes. Participants' open-ended responses were coded into categories for a thematic analysis, which informed a subsequent content analysis of the resulting qualitative data. Content analysis has been beneficial for summarizing and drawing inferences about respondents' communications, usage habits, and communication outcomes (Brandtzæg, 2009).

3.12 Reliability and Validity

Bell and Waters (2018) define validity as the degree to which a research instrument measures what it was intended to measure, i.e., the research questions, hypothesis, or objectives.

Reliability pertains to the extent to which the research problem is accurately and consistently addressed by the study instrument(s). This study used a validity test strategy known as "judging by a panel" to confirm the accuracy of the findings. The experts on a particular subject are surveyed for their opinions on the validity of the study instrument in light of the research questions (Bell & Waters, 2018).

The test-retest reliability approach was employed to ensure the validity of this study, with a pilot study involving ten students serving as a pre-test of data collection tools.

"Pretesting is a crucial stage that needs to be carried out" since it “helps in guaranteeing that all kinds of errors that can be encountered during a survey research are reduced” (Zawacki-Richter et al., 2019, p. 127). It aids in clearing the questionnaire of any potential biases or ambiguities (Battineni et al., 2020). Cronbach's alpha was also used as a reliability test in this study.

3.13 Ethical Considerations

Ethical considerations must be taken into account in all formal studies. To give just one example, a researcher must honestly report the results of their research with the utmost integrity. The researcher must always protect the dignity and safety of the study's subjects and never violate their privacy.

This study was conducted per the University of KwaZulu-Natal ethical guidelines, including submitting an application for Ethical Clearance (EC) to the University's Ethics Committee (Appendix 1 containing the EC letter). The acquired information was treated with strict confidentiality and honesty. The dissertation does not include any details that may be used to identify the individuals. After five years, the questionnaires collected will be destroyed and not used for anything.

3.14 Chapter Summary

The research methods used in this study are outlined in this section. Details on the study's population and the methods used to determine the study's sample size were presented in this chapter. Furthermore, this chapter included in-depth descriptions of the steps taken to create the research instrument, collect data, and analyze results. The chapter details the procedures to ensure the research questionnaire was valid and reliable and how the study met all applicable ethical standards. The study's results will be presented in the next chapter.

Chapter 4 – Results and Discussion

4.1 Introduction

The research methodology was described in the preceding chapter. The results of the student questionnaire survey and their analysis in light of the study's objectives are presented and discussed in this chapter. Descriptive statistics based on the gathered information were also presented in this chapter. The tables and charts generated by IBM SPSS are used to compile the data collected from the surveys, verified by the literature discussed in chapter two.

To begin the scientific portion of the present investigation, the research technique used has been discussed in the preceding chapter. The research was conducted with the following aims in mind, and these aims inform the presentation and analysis of the results:

- To determine students' **behavioural intention to use** a chatbot to assist with **online registration** at UKZN.
- To determine students' **behavioural intention** to use a chatbot to assist with **online learning** (at UKZN via the Learn2022 LMS).
- To leverage students' **experiential knowledge** of using the Msizibot at UKZN to provide support for online registration at UKZN, be used to identify factors that will contribute to greater adoption of chatbot technology to support academic online academic registration.
- To leverage students' **experiential knowledge** of using a chatbot for online learning to improve students' adoption of the Msizibot to facilitate online learning via the UKZN LMS.

The information is broken down into three sections. The first section of the chapter displays the data with bar charts showing frequency and percentages. The presentation of the findings using descriptive statistics constitutes the second section. The final section discusses the presentation of inferential statistics-based results. The selection of the 378 participants is detailed in Chapter 3. The researcher distributed 380 questionnaires. The respondents returned 232 questionnaires for a total response rate of 61%.

4.2 Response rate

Over 380 surveys were sent to the study's sample population, but only 232 complete surveys were returned for analysis. A 61 percent response rate is acceptable (Dillman, 2011; Fincham, 2008).

The response rate was increased through the following means:

- The cover letter demonstrated collective interest in the responders.
- The questionnaire was composed in clear (comprehensible) English and
- The survey was kept to an appropriate duration for a project of this kind.

4.3 Reliability and Validity

Internal consistency and reliability were evaluated using Cronbach's alpha in this study. Mohamad et al. (2015) stress the significance of reliability in research. Consistent performance over time is defined as reliability. Cronbach's alpha is often used in reliability analysis. Lee Cronbach devised an index of internal consistency for scales called Cronbach's alpha in 1951 (Tavakol & Dennick, 2011). "Internal consistency" describes how well a test measures the target construct (Cronbach, 1951). A coefficient near 1 indicates high levels of internal consistency in a research instrument (Mathur et al., 2019). Coefficients (alpha values) in the 0.7–0.9 range are generally considered reliable in scientific studies (Gliem & Gliem, 2003; Pallant, 2013).

The composite Cronbach alpha coefficient was 0.903 after testing the reliability of the questionnaire's 17 items in IBM SPSS for *online registration*. In addition, the composite Cronbach alpha coefficient was 0.951 after trying the reliability of the questionnaire's 17 items in IBM SPSS for *online learning*. The individual constructs based on the UTAUT model were also tested for internal consistency and the resulting outputs are shown in Table 4.1 and Table 4.2. For each major dimension of the study (online registration and online learning) the Cronbach alpha values show a high level of internal consistency for the UTAUT-based constructs,

Table 4.1: Reliability and Consistency statistics (***online registration***)

Item Category	Number of Items in construct	Cronbach's Alpha	No. of Items Tested
PE	4	0.812	4
EE	4	0.743	4
SI	3	0.855	3
BI	2	0.972	2

Table 4.2: Reliability and Consistency statistics (***online learning***)

Item Category	Number of Items in construct	Cronbach's Alpha	No. of Items Tested

PE	4	0.740	3
EE	4	0.754	4
SI	3	0.888	3
BI	2	0.711	2

4.4 Demographics of the Study's Respondents

As illustrated in Figure 4.1, most responders were female (51%), while only 48% were male. This suggests that female students were slightly more prevalent than male students in this survey. Also, 1% of the students identified themselves as gender neutral.

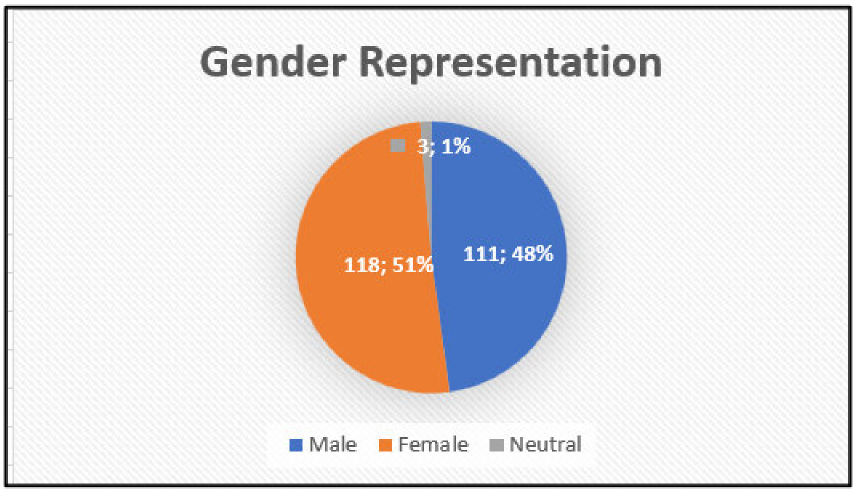

Figure 4.1: Demographic Information: Gender of Respondent

In terms of age classifications, Figure 4.2 shows that all participants were between the ages of 18 and 23. According to the South African Youth Policy, it becomes quite clear that all the respondents fall into an age bracket often associated with youth (South Africa Youth Policy, 2008). All respondents were active UKZN students who utilized the Msizibot (following the study's guidelines for participants).

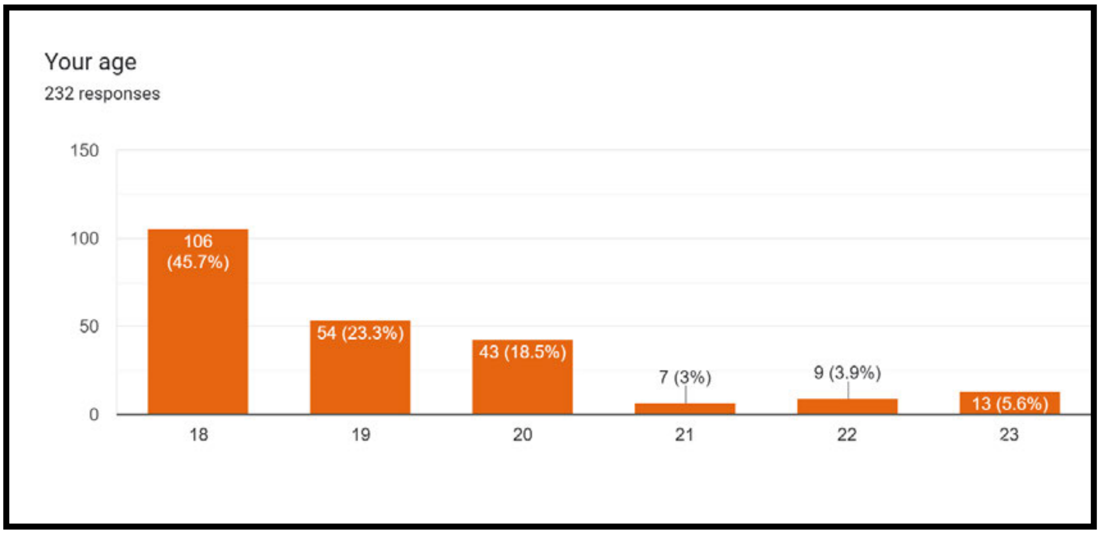

Figure 4.2: Demographic Information: Age of respondents

The illustration in Figure 4.3 shows the academic year of study which indicates that a majority of the students (64%) who did take the survey were first year students.

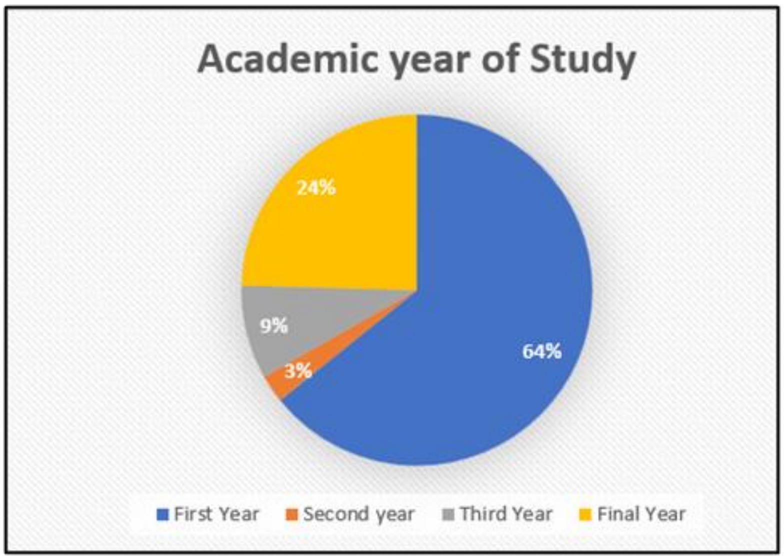

Figure 4.3: Academic Year of Study

In Figure 4.3, it can be seen that there just 3% representation from the 2nd year group, 9% from the 3rd year group and 24% from the final year group. The final year group represented students who were final year BCom Law (LLB) and final year BCom Honours students.

4.5 Responses based on Technology Adoption Constructs

This research has collected its results through four constructs based on the UTAUT framework. The questionnaire consisted of various segments that examined performance expectancy, effort expectancy, social influence, and behavioural intention to use. The outcomes are depicted using a graphical representation and a 5-point Likert scale that ranges from "Strongly Agree" to "Strongly Disagree."

This section of the data analysis will be presented from a dual perspective. The 1st part will provide an illustration and analysis of responses that pertain to online registration. The 2nd section of the presentation will illustrate and analyse responses that pertain to online learning.

4.5.1 How do technology acceptance factors link to students' behavioural intention to use a chatbot to assist with online registration at UKZN?

4.5.1.1 Performance Expectancy (PE)

This study component aimed to gauge the degree to which respondents anticipated efficiency, productivity, and service quality improvements due to adopting Msizibot at the university for online registration. The Likert Scale responses have been converted into a graphical form and shown in Figure 4.4.

Figure 4.4: Performance Expectancy for online registration

As can be observed in Figure 4.4, the results are showing a general positive tendency towards the use of Msizibot in terms of the expected performance of using this facility to enhance productivity from an online registration perspective. The preceding claim is verified by conflating the *Strongly Agree* and *Agree* responses into a classification named *Positive* and the *Strongly Disagree* and *Disagree* responses into a classification named *Negative*. An illustration that provides a graphical version of this summarised computation is shown in Figure 4.5.

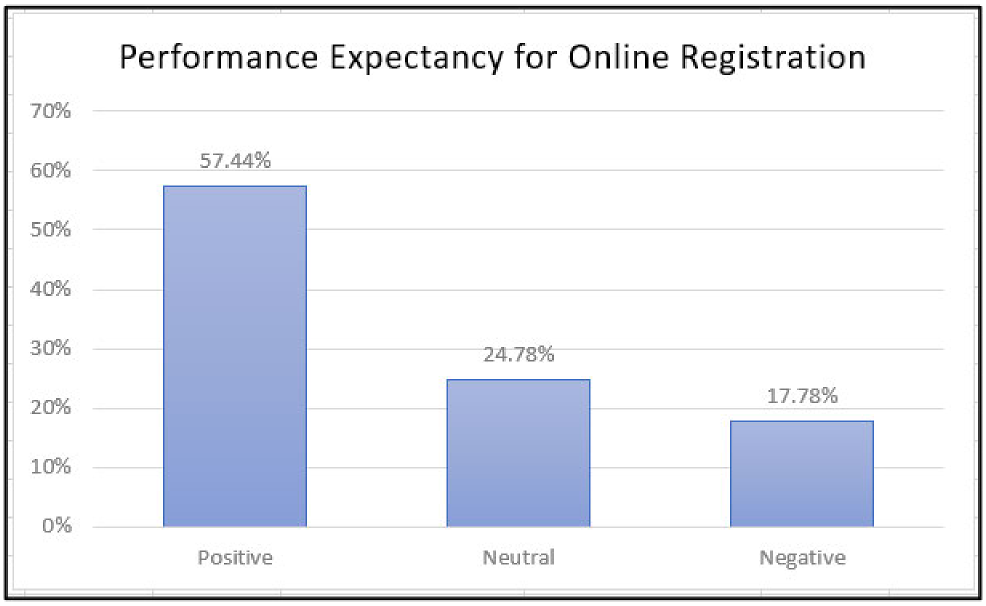

Figure 4.5: Summarised Performance Expectancy for online registration

In Figure 4.5, a majority of the respondents (57%) showed a positive disposition towards PE in using Msizibot for online registration. There was also a moderate (25%) cohort of responses that were neutral and 18% were of the opinion that Msizibot did not enhance performance for registration activity.

4.5.1.2 Effort Expectancy (EE)

This component of the study intended to determine whether or not respondents were confident in their ability to access and use the chatbot system based on their level of familiarity with computers, their level of computer literacy, and the ease of use of the chatbot for online registration. The individual Likert Scale responses for EE have been converted into a graphical form and shown in Figure 4.6.

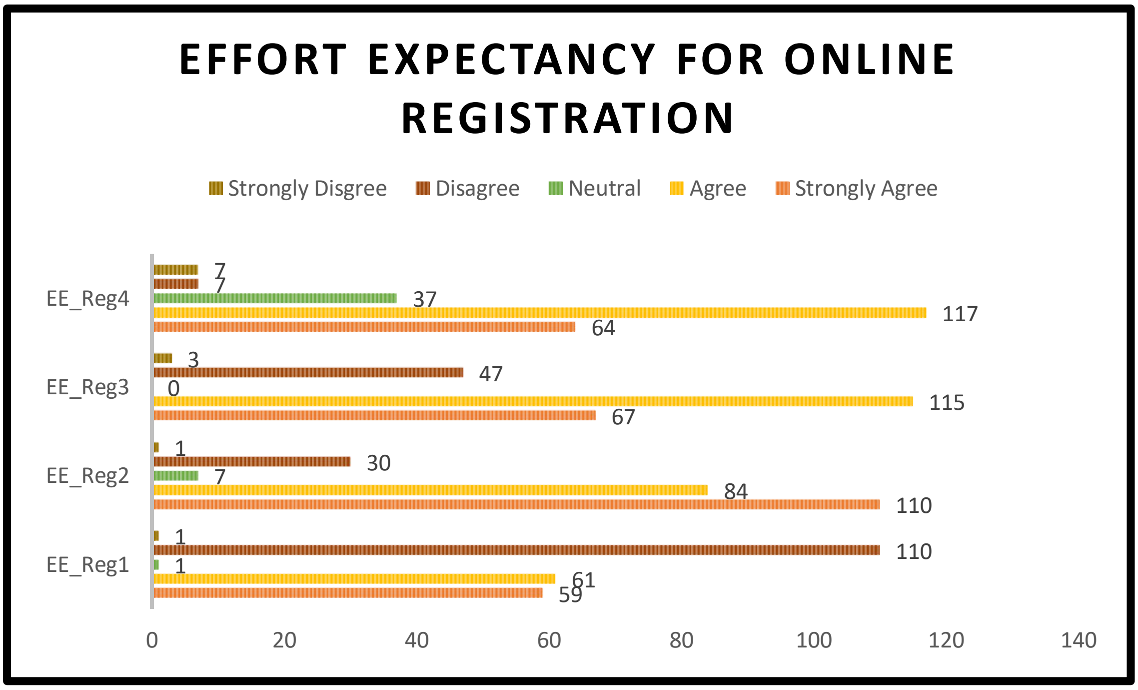

Figure 4.6: Effort Expectancy for online registration

Figure 4.6 illustrates a generally a noticeable positive inclination in terms of the effort required to use Msizibot to enhance the experience of online registration. This assertion is substantiated by conflating the Likert Scale responses into Positive, Neutral and Negative. Figure 4.7 presents a visual representation of this condensed analysis.

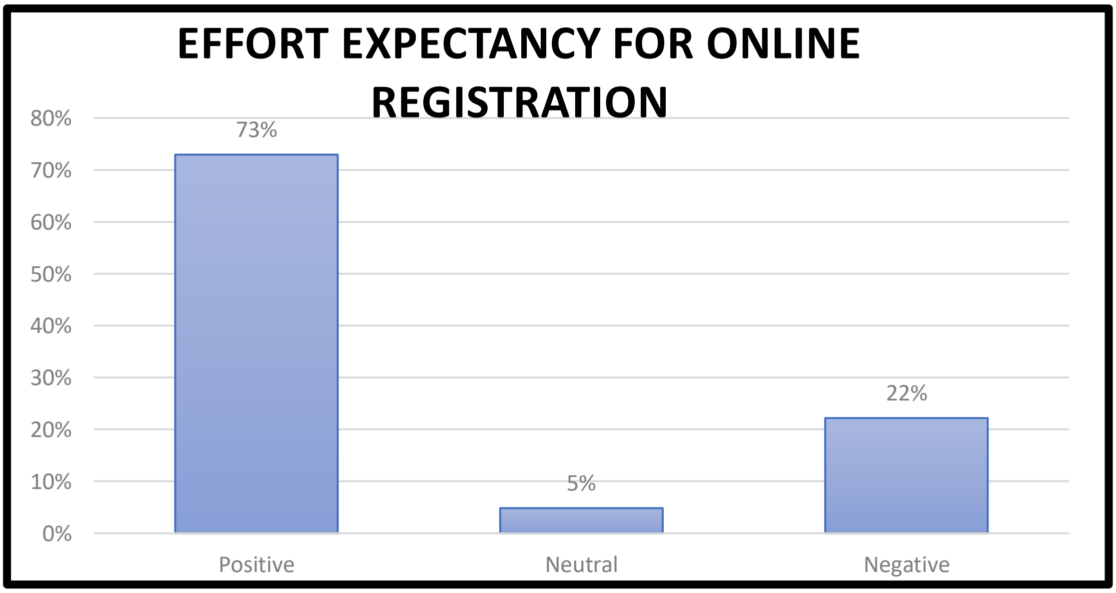

Figure 4.7: Summarised Effort Expectancy for online registration

In Figure 4.7, it can be verified that a majority of the respondents (73%) showed a positive disposition towards the effort required (EE) in using Msizibot for online registration. There was also a moderate (22%) cohort of responses that was negative and 5% were neutral on this aspect of using Msizibot.

4.5.1.3 Social Influence (SI)

In UTAUT, the term "social influence" (SI) refers to an individual's estimation of how much weight other people give their opinion when it comes to the new system (Venkatesh et al., 2003). This section aimed to ascertain whether respondents' SI influences their plans to implement a specific technological innovation for online registration. The Likert Scale responses are illustrated in Figure 4.8.

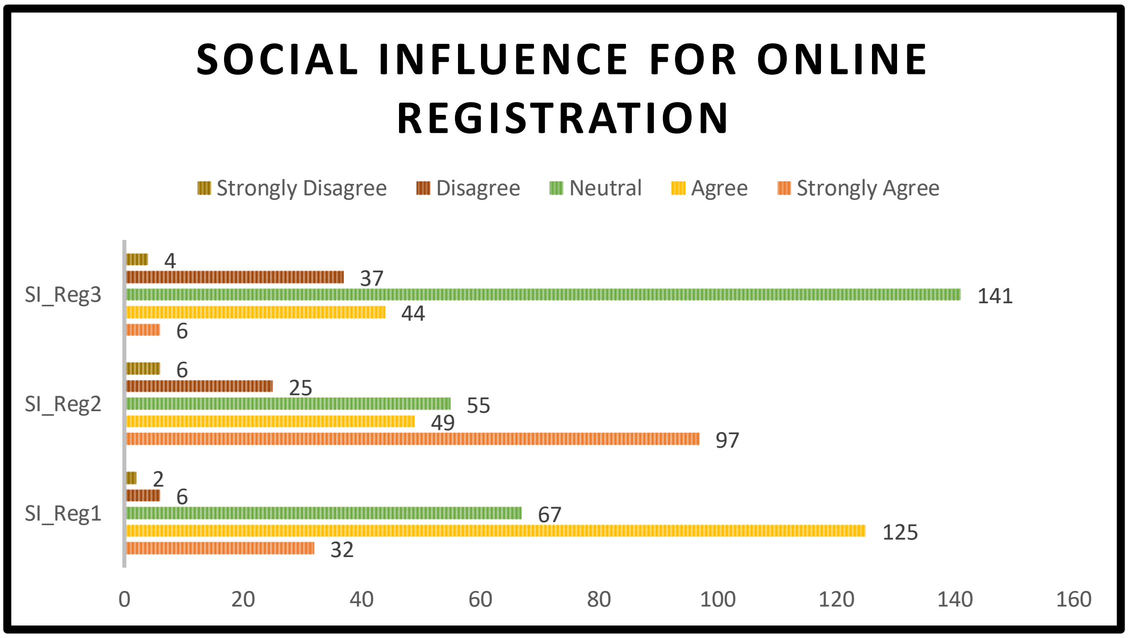

Figure 4.8: Social Influence for online learning

A condensed version of the responses illustrated in Figure 4.8 is shown in Figure 4.9. In Figure 4.9, it can be verified that a majority of the respondents (51%) were of the opinion that their use of Msizibot has been influenced by their social environment. However, significant proportion of the respondents (38%) was neutral with regards to social influence and 11% were of the opinion that their social environment did not influence their preference to use Msizibot.

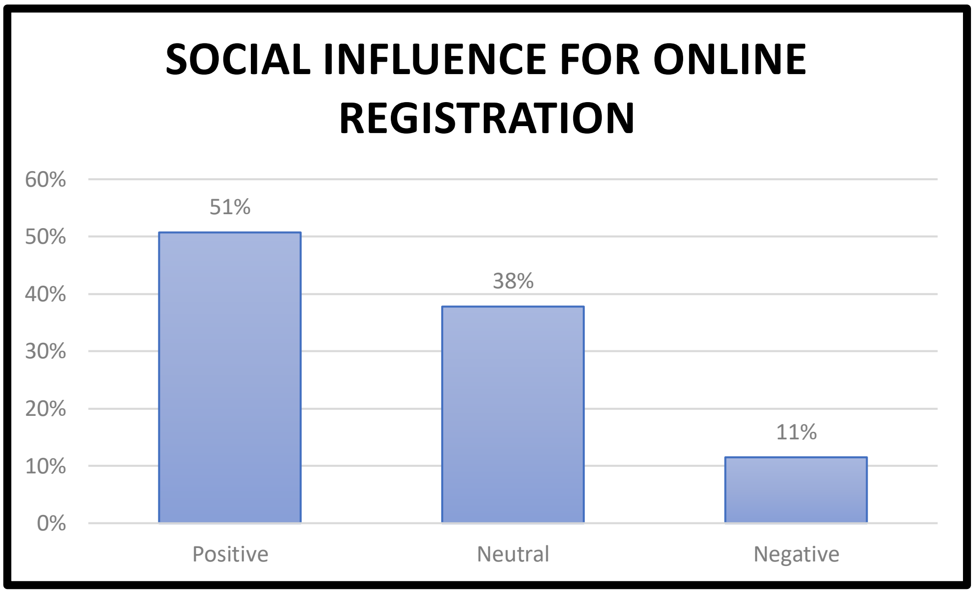

Figure 4.9: Summarised Social Influence for Online Registration

4.5.1.5 Behavioural Intention

The term "behavioural intention" describes the degree to which an individual consciously plans to perform, or refrain from performing, a given action in the future (Davis, 1989).

This concept was examined to learn whether or not students planned to increase their use of the Msizibot in the future for online registration.

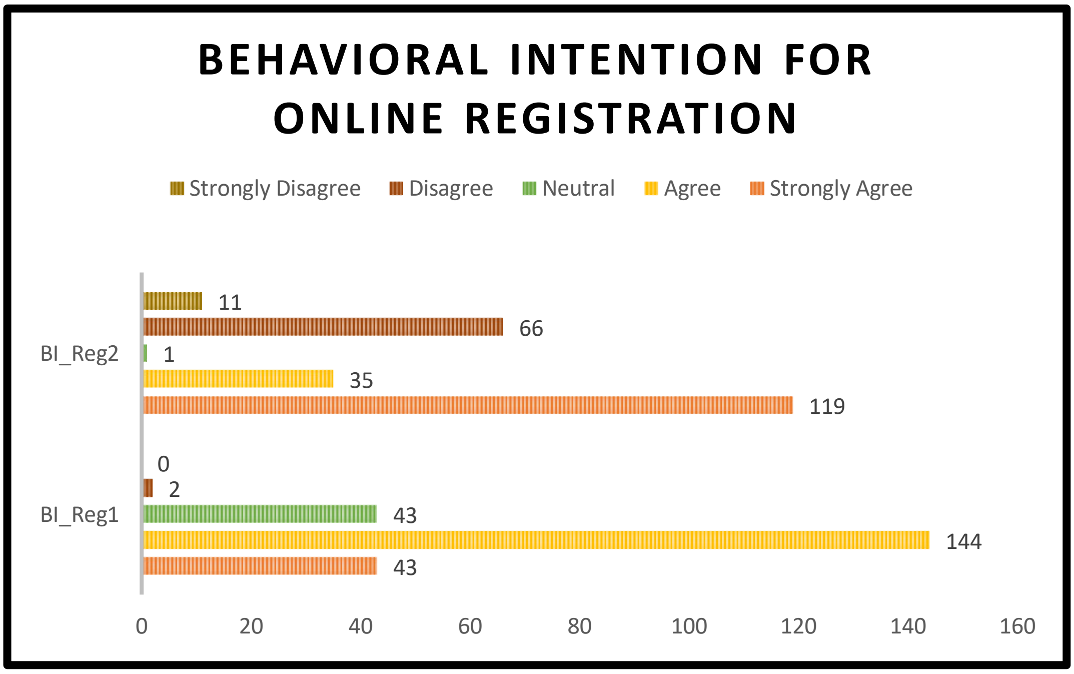

Figure 4.10: Behavioural Intention for online registration

A summarised version of the responses illustrated in Figure 4.10 is shown in Figure 4.11. In Figure 4.11, it can be verified that a majority of the respondents (73%) were of the opinion that their use of Msizibot affected their intention to use the chatbot. However, significant proportion of the respondents (17%) was of the opinion that that will not be using the chatbot in the future. While 9% were neutral to the Msizibot's usage.

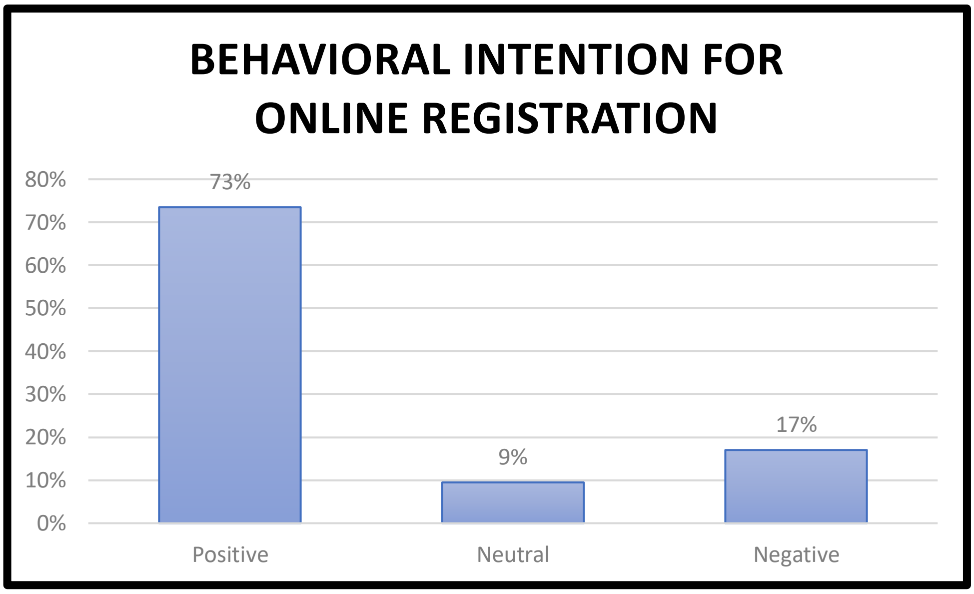

Figure 4.11: Summarised Behavioural Intention for Online Registration

4.5.2 How do technology acceptance factors link to students' behavioural intention to use a chatbot to enhance their online learning experience?

4.5.2.1 Performance Expectancy

This study component aimed to gauge the degree to which respondents anticipated efficiency, productivity, and service quality improvements due to adopting Msizibot at the university for online registration.

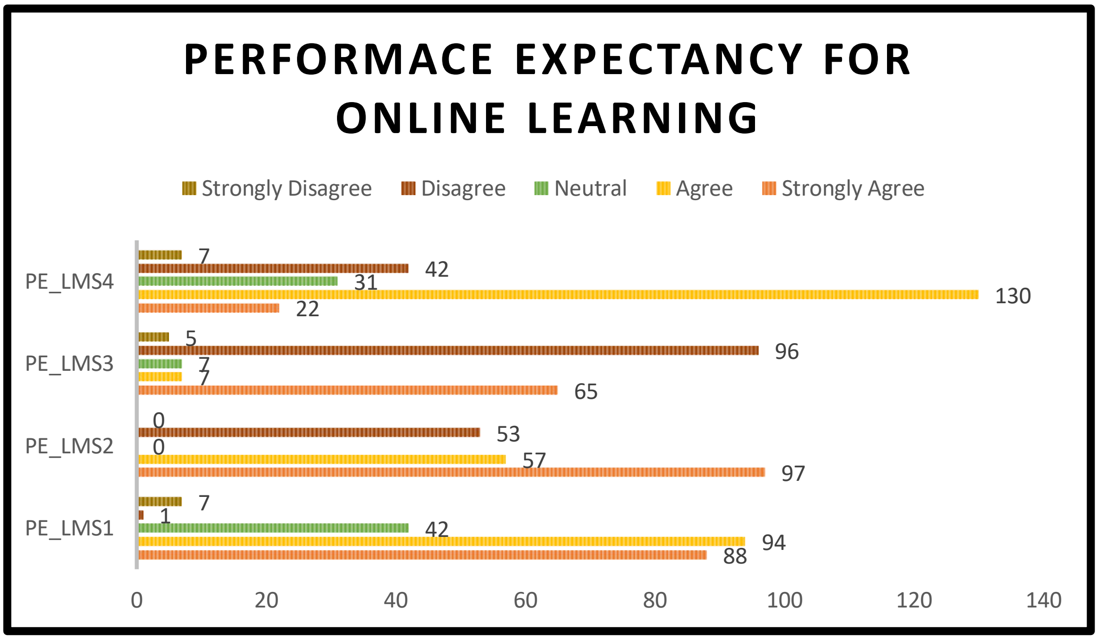

Figure 4.12: Performance Expectancy for online learning

In Figure 4.13, a majority of the respondents (60%) showed a positive disposition towards PE in using Msizibot for online learning. There was also a small (9%) cohort of responses that were neutral and 18% were of the opinion that Msizibot did not enhance performance for online learning activity.

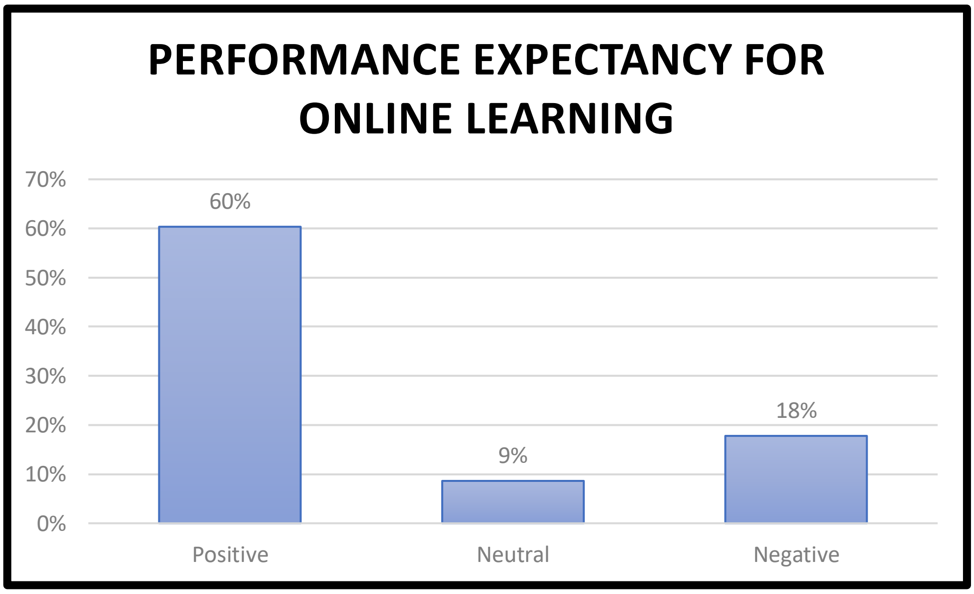

Figure 4.13: Summarised Performance Expectancy for Online Learning

The results are showing a general positive tendency towards the use of Msizibot in terms of the expected performance of using this facility to enhance productivity from an online learning perspective, as illustrated in Figure 4.1.3

4.5.2.2 Effort Expectancy

The purpose of this section of the study was to ascertain whether or not respondents felt comfortable with the chatbot system, taking into account the respondents' experience with computers, computer literacy, and the chatbot's ease of use for online learning.

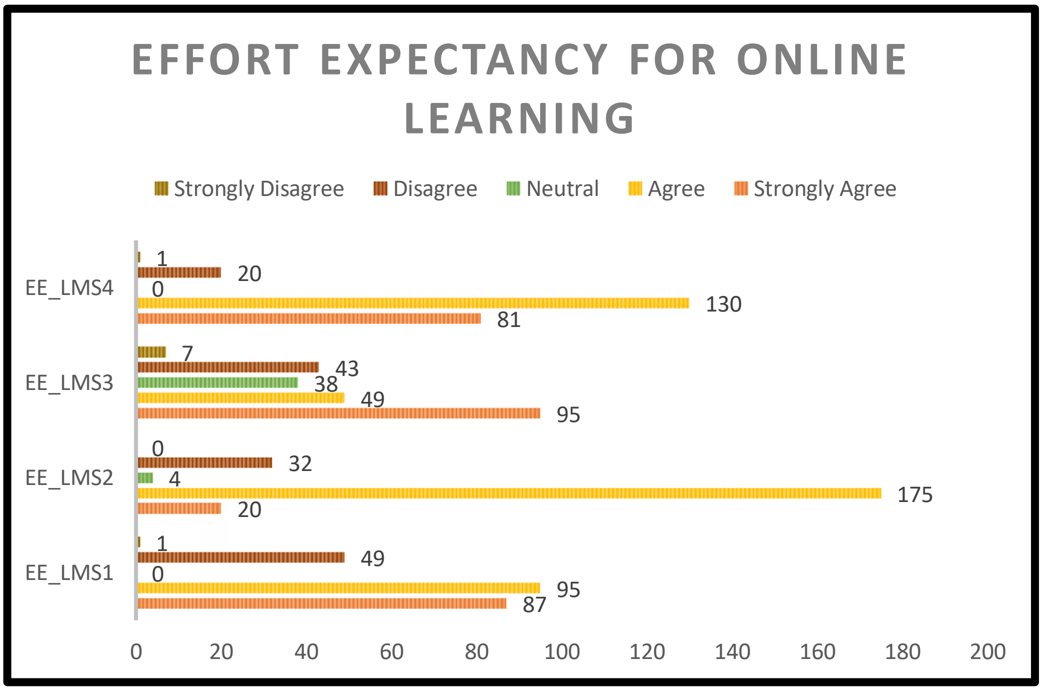

Figure 4.14: Effort Expectancy for online learning

In Figure 4.15, it can be verified that a majority of the respondents (79%) showed a positive disposition towards the effort required (EE) in using Msizibot for online learning. There was also a small (5%) cohort of responses that was negative and 17% were neutral on this aspect of using Msizibot.

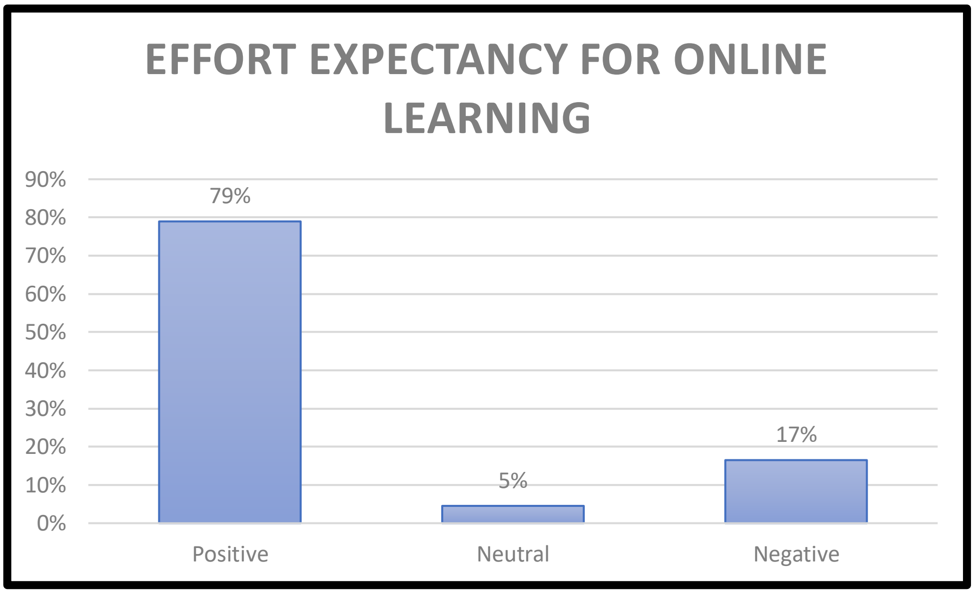

Figure 4.15: Summarised Effort Expectancy for Online Learning

4.5.2.3 Social Influence

This section aimed to learn if respondents' SI affected their likelihood of adopting a new registration technology for online learning.

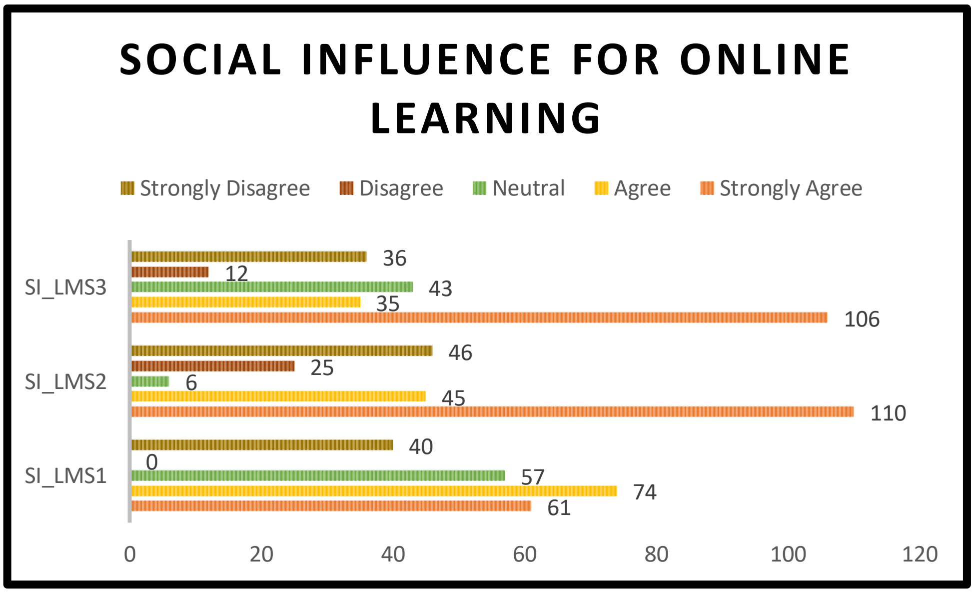

Figure 4.16: Social Influence for online learning

Similar to the survey conducted in the current study on SI for online registration, most respondents agreed that the chatbot application's popularity among their peers was a major motivating factor in their decision to use it. A condensed version of the responses illustrated in Figure 4.16 is shown in Figure 4.17. In Figure 4.17, it can be verified that a majority of the respondents (62%) were of the opinion that their use of Msizibot has been influenced by their social environment. In addition, a significant proportion of the respondents (23%) were of the opinion that their social environment did not influence their preference to use Msizibot and some respondents were neutral with regards to social influence at 11% .

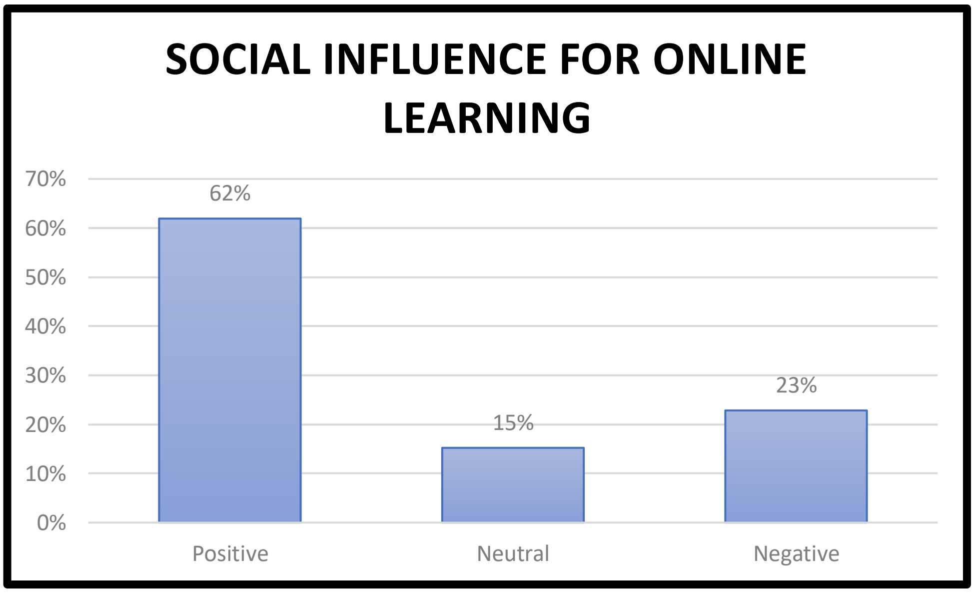

Figure 4.17: Summarised Social Influence for Online Learning

4.5.2.5 Behavioural Intention

The term "behavioural intention" describes the degree to which an individual consciously plans to perform, or refrain from performing, a given action in the future (Davis, 1989).

This notion was investigated to determine whether or not students intended to increase their use of the Msizibot for online registration in the future.

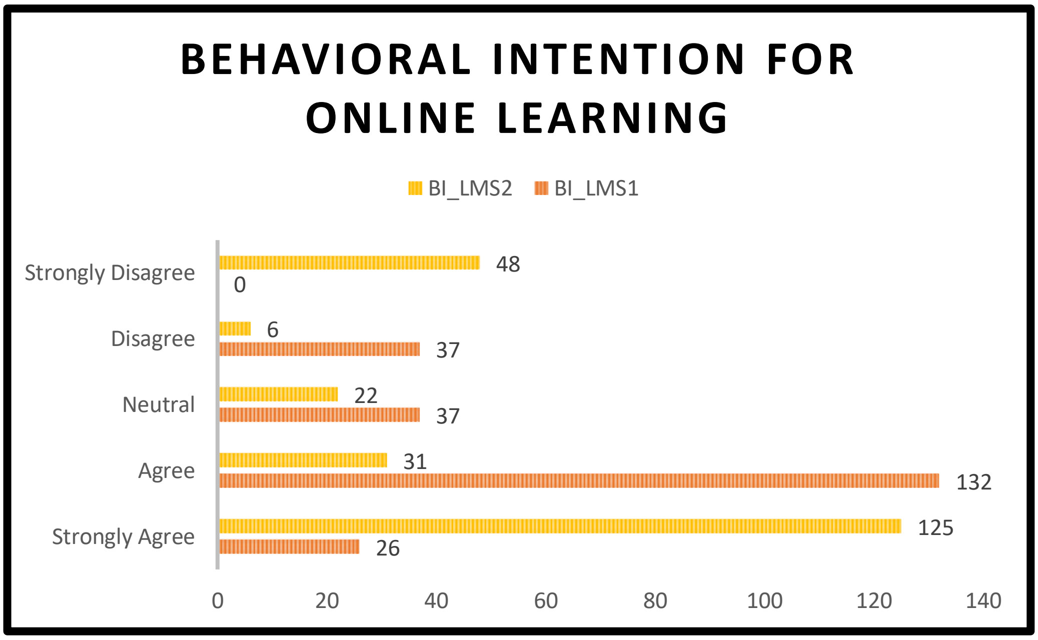

Figure 4.18: Behavioral Intention for Online Learning

Similar to the survey conducted in the current study on BI for online registration, most respondents agreed that they would continue to use the chatbot application in the future.

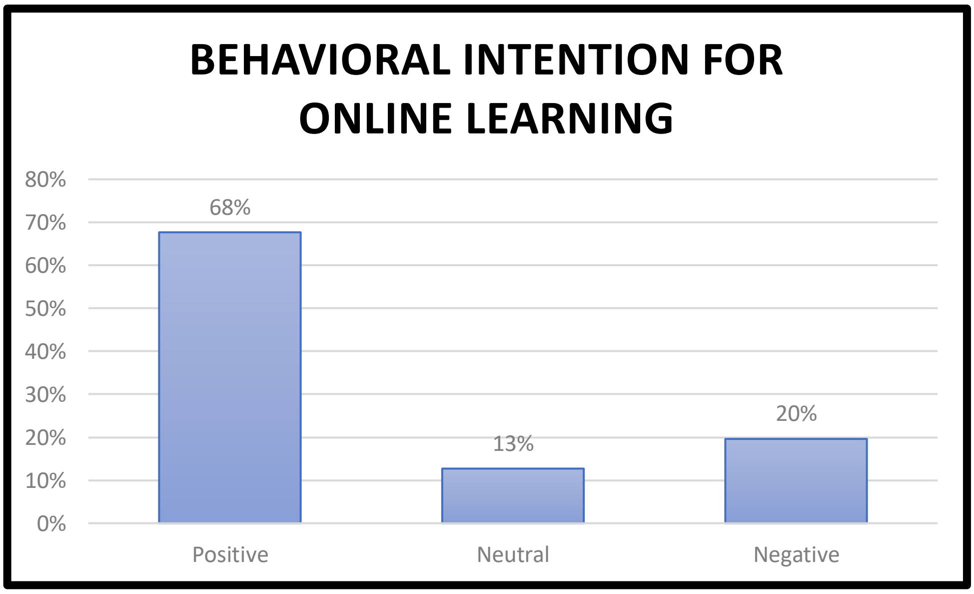

Figure 4.19: Summarised Behavioral Intention for Online Learning

A summarised version of the responses illustrated in Figure 4.18 is shown in Figure 4.19. In Figure 4.19, it can be verified that a majority of the respondents (68%) were of the opinion that their use of Msizibot affected their intention to use the chatbot for online learning. However, significant proportion of the respondents (20%) was of the opinion that that will not be using the chatbot in the future. While nine percent were neutral to the Msizibot's usage.

4.6 T-test Analysis for Significance of the Means

According to Saunders et al. (2009), once a study's descriptive statistics have been presented, it is incumbent upon the researcher to ensure that the aggregated data analysis of the sample data is not due to chance and these results are a significant representation of the statistic that is being reported. In the context of the current study, the preceding statistical analysis provided an indication of the overall interpretation of the data by using percentages and a frequency graph to show the dominant trends in the data. However, this interpretive strategy will be replaced by a calculation of the mean value for the responses to the survey questionnaire items. The t-test is used to determine whether the mean value that is computed is a significant representation of the study's data from an aggregated perspective. The questionnaire's acceptance variables were evaluated by determining the average response to each question and assessing whether there was a statistically significant agreement or discordance. A neutral value of 3 was used to compare the participants' answers, a widely accepted approach proposed by Wu et al. (2012). The t-test was employed to investigate the deviation of the mean response from the neutral value of 3. However, these results will be presented in the body of the text to contextualise the discussion that follows. It should be noted that mean values less than 3 indicate data patterns that favour a positive response to the construct being measured because the questionnaire items were phrased positively towards the effectiveness of using Msizibot for online registration and online learning.

4.6.1 T-test of Significance for PE in using Msizibot for Online Registration

In Table 4.3, the mean values for Performance Expectancy (PE) for online registration are shown. As shown in Table 4.3, all the mean values for the construct of PE are lower than the neutral value of 3 (M<3), suggesting an overall positive rating by the respondents towards the chatbot.

Table 4.3: Mean for PE Online Registration

One-Sample Mean for PE Online Registration				
	N	Mean	Std. Deviation	Std. Error Mean
PE_Reg1	232	2.22	.994	.065
PE_Reg2	232	2.81	1.344	.088
PE_Reg3	232	1.98	1.113	.073
PE_Reg4	232	2.48	1.116	.073

Each of these mean values reported in Table 4.3 were subjected to the t-test of significance and as can be seen in Table 4.4, all the mean values are shown to be significant ($p<0.05$)

Table 4.4: T-Test of Significance for PE - Online Registration

	t	df	Significance		Mean Difference
			One-Sided p	Two-Sided p	
PE_Reg1	-11.886	231	<,001	<,001	-.776
PE_Reg2	-2.101	231	.018	.037	-.185
PE_Reg3	-13.927	231	<,001	<,001	-1.017
PE_Reg4	-7.116	231	<,001	<,001	-.522

4.6.2 T-test of Significance for EE in using Msizibot for Online Registration

Table 4.5 presents the average scores indicating Effort Expectancy (EE) for online registration. The data in Table 4.5 reveals that all the mean values associated with the EE construct are below the neutral value of 3 (M<3), implying a generally favourable assessment of the chatbot by the survey participants.

Table 4.5: Mean for EE - Online Registration

One-Sample Mean for EE Online Registration				
	N	Mean	Std. Deviation	Std. Error Mean
EE_Reg1	232	2.71	1.302	.085
EE_Reg2	232	1.83	1.017	.067
EE_Reg3	232	2.16	1.094	.072
EE_Reg4	232	2.03	.911	.060

The significance of each of the mean values reported in Table 4.5 was evaluated using a t-test. As depicted in Table 4.6, all of the mean values demonstrated statistical significance ($p<0.05$), indicating that they are unlikely to have occurred by chance.

Table 4.6: T-Test of Significance for EE - Online Registration

	t	df	Significance		Mean Difference
			One-Sided p	Two-Sided p	
EE_Reg1	-3.378	231	<,001	<,001	-.289
EE_Reg2	-17.552	231	<,001	<,001	-1.172
EE_Reg3	-11.764	231	<,001	<,001	-.845
EE_Reg4	-16.143	231	<,001	<,001	-.966

4.6.3 T-test of Significance for SI in using Msizibot for Online Registration

Table 4.7 displays the mean values for Social Influence (SI) concerning online registration. Notably, all the mean values associated with the SI construct, as presented in Table 4.4, indicate a rating lower than the neutral value of 3 (M<3). This observation implies that the respondents generally are influenced to use the chatbot in their environment.

Table 4.7: Mean for SI - Online Registration

One-Sample Mean for SI Online Registration				
	N	Mean	Std. Deviation	Std. Error Mean
SI_Reg1	232	2.23	.747	.049
SI_Reg2	232	2.11	1.145	.075
SI_Reg3	232	2.95	.722	.047

The statistical significance of each mean value reported in Table 4.7 was assessed through a t-test. As illustrated in Table 4.8, two of the mean values exhibited a significant level of statistical significance ($p<0.05$). This finding suggests that the observed results are highly unlikely to have been obtained by chance.

Table 4.8: T-Test of Significance for SI - Online Registration

			Significance		
	t	df	One-Sided p	Two-Sided p	Mean Difference
SI_Reg1	-15.733	231	<,001	<,001	-.772
SI_Reg2	-11.807	231	<,001	<,001	-.888
SI_Reg3	-1.000	231	.159	.318	-.047

4.6.5 T-test of Significance for BI to use Msizibot for Online Registration

Table 4.9 displays the mean values representing Behavvioral Intention (BI) in the context of online registration. As evident from the table, all the mean values associated with the BI construct are below the neutral threshold of 3 (M<3), indicating an overall positive rating attributed by the respondents to the chatbot. This observation suggests that the participants hold favorable perceptions regarding the students intention to use the chatbot in the future.

One-Sample Mean for BI to use Msizibot for Online Registration				
	N	Mean	Std. Deviation	Std. Error Mean
BI_Reg1	232	2.02	.638	.042
BI_Reg2	232	2.20	1.432	.094

Table 4.9: Mean for BI Online Registration

A comprehensive assessment of significance was conducted for each mean value reported in Table 4.9 using a t-test. The outcomes, as illustrated in Table 4.10, demonstrate that all of the mean values reached statistical significance ($p<0.05$). This indicates that the observed results are highly unlikely to have occurred by chance alone. Consequently, these findings provide robust evidence supporting the validity and reliability of the study's outcomes.

	t	df	Significance		Mean Difference
			One-Sided p	Two-Sided p	
BI_Reg1	-23.474	231	<,001	<,001	-.983
BI_Reg2	-8.484	231	<,001	<,001	-.797

Table 4.10: T-Test of Significance for BI - Online Registration

4.6.6 T-test of Significance for PE in using Msizibot for Online Learning

In Table 4.11, the mean values for Performance Expectancy (PE) for online learning are shown. As shown in Table 4.3, all the mean values for the construct of PE are lower than the neutral value of 3 ($M<3$), suggesting an overall positive rating by the respondents towards the chatbot.

Table 4.11: Mean for PE - Online Learning

One-Sample Mean for PE Online Learning	N	Mean	Std. Deviation	Std. Error Mean
PE_LMS1	232	1.90	.918	.060
PE_LMS2	232	2.36	1.476	.097
PE_LMS3	232	2.64	1.325	.087
PE_LMS4	232	2.49	.993	.065

Each of these mean values reported in Table 4.11 were subjected to the t-test of significance and as can be seen in Table 4.12, all the mean values are shown to be significant ($p<0.05$)

Table 4.12: T-Test of Significance for PE - Online Learning

	t	df	Significance		Mean Difference
			One-Sided p	Two-Sided p	
PE_LMS1	-18.235	231	<,001	<,001	-1.099
PE_LMS2	-6.581	231	<,001	<,001	-.638
PE_LMS3	-4.114	231	<,001	<,001	-.358
PE_LMS4	-7.798	231	<,001	<,001	-.509

4.6.7 T-test of Significance for EE in using Msizibot for Online Learning

Table 4.13 presents the average scores indicating Effort Expectancy (EE) for online learning. The data in Table 4.13 reveals that all the mean values associated with the EE construct are below the neutral value of 3 (M<3), implying a generally favorable assessment of the chatbot by the survey participants.

Table 4.13: Mean for EE - Online Learning

One-Sample Mean for EE Online Learning				
	N	Mean	Std. Deviation	Std. Error Mean
EE_LMS1	232	2.06	1.123	.074
EE_LMS2	232	2.22	.805	.053
EE_LMS3	232	2.22	1.244	.082
EE_LMS4	232	1.84	.842	.055

Each of these mean values reported in Table 4.13 were subjected to the t-test of significance and as can be seen in Table 4.14, all the mean values are shown to be significant ($p<0.05$)

Table 4.14: T-Test of Significance for EE - Online Learning

			Significance		
	t	df	One-Sided p	Two-Sided p	Mean Difference
EE_LMS1	-12.748	231	<,001	<,001	-.940
EE_LMS2	-14.757	231	<,001	<,001	-.780
EE_LMS3	-9.609	231	<,001	<,001	-.784
EE_LMS4	-21.052	231	<,001	<,001	-1.164

4.6.8 T-test of Significance for SI in using Msizibot for Online Learning

Table 4.15 displays the mean values for Social Influence (SI) concerning online learning. Notably, all the mean values associated with the SI construct, as presented in Table 4.15, indicate a rating lower than the neutral value of 3 (M<3). This observation implies that the respondents generally are influenced to use the chatbot in their environment.

Table 4.15: Mean for SI - Online Learning

One-Sample Mean for SI Online Learning				
	N	Mean	Std. Deviation	Std. Error Mean
SI_LMS1	232	2.50	1.348	.089
SI_LMS2	232	2.36	1.611	.106
SI_LMS3	232	2.30	1.472	.097

The statistical significance of each mean value reported in Table 4.15 was assessed through a t-test. As illustrated in Table 4.16, two of the mean values exhibited a significant level of statistical significance ($p<0.05$).

Table 4.16: T-Test of Significance for SI - Online Learning

	t	df	Significance		Mean Difference
			One-Sided p	Two-Sided p	
SI_LMS1	-5.648	231	<,001	<,001	-.500
SI_LMS2	-6.031	231	<,001	<,001	-.638
SI_LMS3	-7.270	231	<,001	<,001	-.703

4.6.9 T-test of Significance for BI to use Msizibot for Online Learning

Table 4.17 displays the mean values representing Behavvioral Intention (BI) in the context of online registration. As evident from the table, all the mean values associated with the BI construct are below the neutral threshold of 3 ($M<3$), indicating an overall positive rating attributed by the respondents to the chatbot. This observation suggests that the participants hold favorable perceptions regarding the students intention to use the chatbot in the future.

Table 4.17: Mean for BI - Online Learning

One-Sample Mean for BI to use Msizibot for Online Learning				
	N	Mean	Std. Deviation	Std. Error Mean
BI_LMS1	232	2.37	.882	.058
BI_LMS2	232	2.23	1.599	.105

A comprehensive assessment of significance was conducted for each mean value reported in Table 4.17 using a t-test. The outcomes, as illustrated in Table 4.18, demonstrate that all of the mean values reached statistical significance ($p<0.05$).

Table 4.18: T-Test of Significance for BI - Online Learning

	t	df	Significance		Mean Difference
			One-Sided p	Two-Sided p	
BI_LMS1	-10.937	231	<,001	<,001	-.634
BI_LMS2	-7.348	231	<,001	<,001	-.772

4.7 Pearson Correlation to establish relationships between variables

According to Saunders (2016) the Pearson correlation test is a common statistical test to determine if there is a significant relationship between 2 variables. A point that has been emphasised is this is not necessarily a causal relationship, but simply a test to ascertain whether a variable has an influence on the value observed of another (dependent) variable. The strength of the relationship is expressed using a symbol r that ranges from -1 to +1 and the statistical significance of the relationship is measured using the symbol p where the norm is to achieve a significance level where $p<0.01$ or $p<0.05$ (Sekaran & Bougie, 2016).

The robustness of the Pearson correlation has been analysed in Havlicek and Peterson (1976) as well as (Chok, 2010) and in both these studies it has been confirmed that the data's structure (shape) has minimal bearing on the results reported from the Pearson Correlation test in comparison to other non-parametric equivalent tests such as the Spearman or the Kendall' tau correlation. The argument for the robustness of the Pearson correlation test has been used as a basis from which the correlation analysis for the current study has been conducted.

4.7.1 The Correlation Analysis for Online Registration

The UTAUT theoretical model was used to operationalize the concept of Msizibot acceptance, with its independent variables including performance expectancy (PE), effort expectancy (EE), and social influence (SI). The dependent variable is the behavioural intention (BI) to continue using Msizibot for online registration. A Pearson's correlation calculation was conducted to determine the independent factors' potential influence on the behavioural intention (BI) of the study's respondents to continue using Msizibot for assistance with online registration.

The UTAUT constructs were arranged in a relationship where PE, EE, and SI were identified as independent variables and BI was identified as the dependent variable. While this relationship between the independent and dependent variables was the main focus of this analysis, the data analytics tool also reported on the inter-variable relationship between all the variables in a matrix format shown in Table 4.19. Table 4.19 represents the correlation analysis for online registration only.

Table 4.19: Correlation matrix between UTAUT constructs and BI for online registration

		PE	EE	SI	BI	Gender
PE	Pearson Correlation	1	.891**	.881**	.931**	-.213
	Sig. (2-tailed)		0.000	0.000	0.000	.061

	N	232	232	232	232	232
EE	Pearson Correlation	.891**	1	.922**	.943**	.273
	Sig. (2-tailed)	0.000		0.000	0.000	.172
	N	232	232	232	232	232
SI	Pearson Correlation	.881**	.922**	1	.921**	.209
	Sig. (2-tailed)	0.000	0.000		0.000	.123
	N	232	232	232	232	232
BI	Pearson Correlation	.931**	.943**	.921**	1	-.246
	Sig. (2-tailed)	0.000	0.000	0.000		.177
	N	232	232	232	232	232
Gender	Pearson Correlation	-.213	.273	.209	-.246	1
	Sig. (2-tailed)	.061	.172	.123	.177	
	N	232	232	232	232	232

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

The results show the following significant relationship:

- PE and BI had a strong positive correlation (***r*=0.93; *p*<0.01**). This statistic shows that the productivity gains from utilizing the Msizibot have a favourable influence on students' intention to continue using the Msizibot for online registration. This outcome is informed by the analysis component of the Venkatesh (2003) study where correlation analysis was used in a similar manner.
- EE and BI have a strong positive connection (***r*=0.94; *p*<0.01**). This statistic suggests that students' intention to continue using the Msizibot for online registration is positively influenced by the ease of use or the effort it takes to use the Msizibot.
- SI and BI have a strong positive correlation (***r*=0.92; *p*<0.01**). This statistic shows that the influence and attitude of influential persons in the educational environment regarding Msizibot positively impact on students' intention to continue using Msizibot for online registration.

Also, from Table 4.19 it has been observed that there is a non-significant negative correlation between the gender of the respondents and their behavioural intention (BI) to use Msizibot for online registration (***r* = -.246, *p*=.177**). While the study's conceptual framework has excluding mediating variables such as gender, demographic details such as gender has been captured via the study's data collection instrument. This result does confirm the decision to omit gender as an influential construct to understand online registration behaviour of the study's respondents.

4.7.2 The Correlation Analysis for Online Learning

The correlation analysis for online learning has been conducted in a similar manner to the previous section (for online registration) and the outcome of this analysis is shown in Table 4.20.

Table 4.20: The correlation matrix between UTAUT constructs and BI for online learning

		PE	EE	SI	BI	Gender
PE	Pearson Correlation	1	.877**	.941**	.844**	-.231
	Sig. (2-tailed)		0.000	0.000	0.000	.066
	N	232	232	232	232	232
EE	Pearson Correlation	.877**	1	.921**	.836**	.199
	Sig. (2-tailed)	0.000		0.000	0.000	.551
	N	232	232	232	232	232
SI	Pearson Correlation	.941**	.921**	1	.867**	-.137
	Sig. (2-tailed)	0.000	0.000		0.000	.193
	N	232	232	232	232	232
BI	Pearson Correlation	.844**	.836**	.867**	1	-.291
	Sig. (2-tailed)	0.000	0.000	0.000		.035
	N	232	232	232	232	232
Gender	Pearson Correlation	-.231	.199	-.137	-.291	1
	Sig. (2-tailed)	.066	.551	.193	.035	
	N	232	232	232	232	232

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

The results show the following significant relationship:

PE and BI had a strong positive correlation (***r*=0.84; *p*<0.01**). This statistic shows that academic performance gains from utilizing the Msizibot have a favourable influence on students' intention to continue using the Msizibot for online learning. This outcome is informed by the analysis component of the Venkatesh (2003) study where correlation analysis was used in a similar manner.

- EE and BI have a strong positive connection (***r*=0.84; *p*<0.01**). This statistic suggests that ease of use or the effort required to use the Msizibot has a favouarble influence on students' intention users to continue using the Msizibot for online learning.
- SI and BI have a strong positive correlation **(*r*=0.87; *p*<0.01**). This statistic shows that the influence and attitude of influential persons in the academic environment regarding Msizibot positively impacts on students' intention to continue using Msizibot for online learning.

Similar to the online registration correlation results, there was a non-significant negative connection between the gender of the Msizibot and BI to continue using the system ($r = -.291$, $p=.035$). This result does confirm the decision to omit gender as an influential construct to understand online registration behaviour of the study's respondents.

4.8 Analysis of open-ended questions

The qualitative data collected for the study does not form the main corpus of the study's data. However, it has been envisaged that the qualitative data will provide a depth-driven perspective to the quantitative data and will serve as a supplementary resource to support the analysis of the study's quantitative data. The qualitative data analysis has been guided to a certain extent by the generic writing on this topic in Sekaran and Bougie (2016) and (Saunders, 2016). However, detailed guidance has been obtained from Creswell and Poth (2016) as well as Corbin and Strauss (1990) and Richards and Hemphill (2018). The qualitative data has been analysed using in six stages to reveal central recurring themes. These are:

- Data familiarization was accomplished by scanning through the open-ended questionnaire responses (Step 1). An initial set of codes (Corbin & Strauss, 1990) was developed to classify commonly occurring words/themes (Step 2).
- The initial set of classifications were further refined (Step 3) to remove unnecessary material and conflate redundant words/themes into a more succinct set of themes (Step 4).
- The final step (Step 5) was to identify the most appropriate names for the themes in the refined.

4.8.1 How can students' experiential knowledge of using the Msizibot (the current name given to the UKZN chatbot) for online registration be used to enable the adoption of chatbot technology for academic registration at UKZN?

The qualitative data revealed the main overarching themes (Table 4.21), representing the most frequently discussed aspects of the chatbot's performance in disseminating online registration material.

Table 4.21: The category of the themes after thematic analysis

Category	Theme
Positive Viewpoint	The chatbot is easy to use
	Immediate feedback
Negative Viewpoint	There is a shortage of detailed interactions.

Students were generally pleased (positive) with their experiences using the Msizibot for online registration. A few verbatim quotes are provided to indicate to support the themes that have been identified.

The chatbot is easy to use

"I had no idea a chatbot would be so simple to utilize on my phone."

"It was simple to forward the chatbot's responses on WhatsApp to my fellow students. This was helpful because it is the main social media we use."

Immediate feedback

"I got prompt responses to my inquiries on registration fees and accommodation during the day or night."

"I realised how quick the responses are."

The students were pleased with the promptness with which their questions were answered during online chats. In most cases, they favoured employing the chatbot in educational settings. In contrast to their interactions with an administrator, during which their questions might have been answered slowly or not at all. In the case of Msizibot users who asked questions in the chat platform received immediate responses. Notwithstanding this encouraging response, students raised one main concern about the chatbot's role in online registration.

There is a dearth of detailed interactions

"Occasionally, I was given a link or a brief response to my inquiry."

"The chatbot's responses were often too abstract for me to grasp fully; therefore, I wished there were more opportunities for clarification."

Students' complaints regarding the chatbot's lack of in-depth learning were synthesized from the negative responses they provided.

The responses that were classified into these main themes have been quantitively illustrated in Table 4.22.

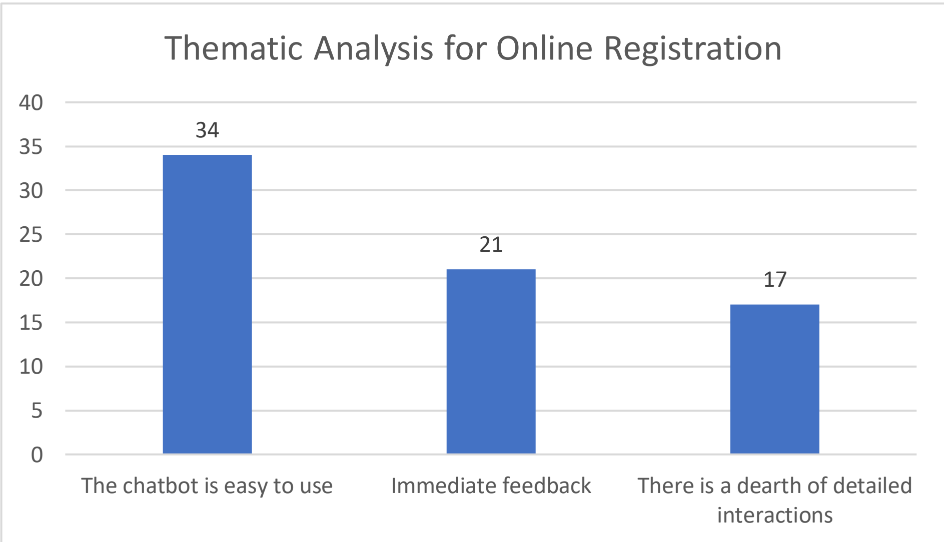

Figure 4.20: Frequency Count of Thematic Analysis for Online Registration

Figure 4.24 suggests that the majority of respondents found the chatbot to be user-friendly, as indicated by the high count for "The chatbot is easy to use." Additionally, a considerable number of respondents appreciated the chatbot's ability to provide immediate feedback. However, a relatively smaller portion of respondents expressed concerns about the lack of detailed interactions with the chatbot.

Overall, the bar graph provides an overview of the main themes identified from the survey responses, highlighting the strengths and areas for improvement for Msizibot in terms of user-friendliness, immediate feedback, and the need for more detailed interactions.

4.8.2 How can students' experiential knowledge of using the Msizibot to facilitate online learning be used to enable the adoption of chatbot technology to support online learning?

The qualitative data revealed two overarching themes (Table 4.22), representing the most frequently discussed aspects of the chatbot's performance in disseminating online learning material.

Table 4.22: Thematic Analysis Classifications for Online Learning

Category	**Theme**
Positive Viewpoint	More self-belief to learn more effectively
Negative Viewpoint	Inability to think in depth

Students were pleased with their experiences using the Msizibot for online learning. Some good student quotes affirming the positive perspectives are provided below.

More self-belief to learn more effectively

"I've learned to rely on my resources."

"At first, I doubted the info I was given, but eventually, I could verify the answer on my own."

Most students were satisfied with the Msizibot for online learning, while few raised one main concern about the chatbot's role in online learning.

Inability to think in depth

“Sometimes, I felt the chatbot's response needed additional context or justification. I was confused about how to use the knowledge provided.”

“At one point, I wished the lecturer had supported the chatbot.

Students' complaints regarding the chatbot's inability to think in-depth about learning were synthesized from the negative responses they provided.

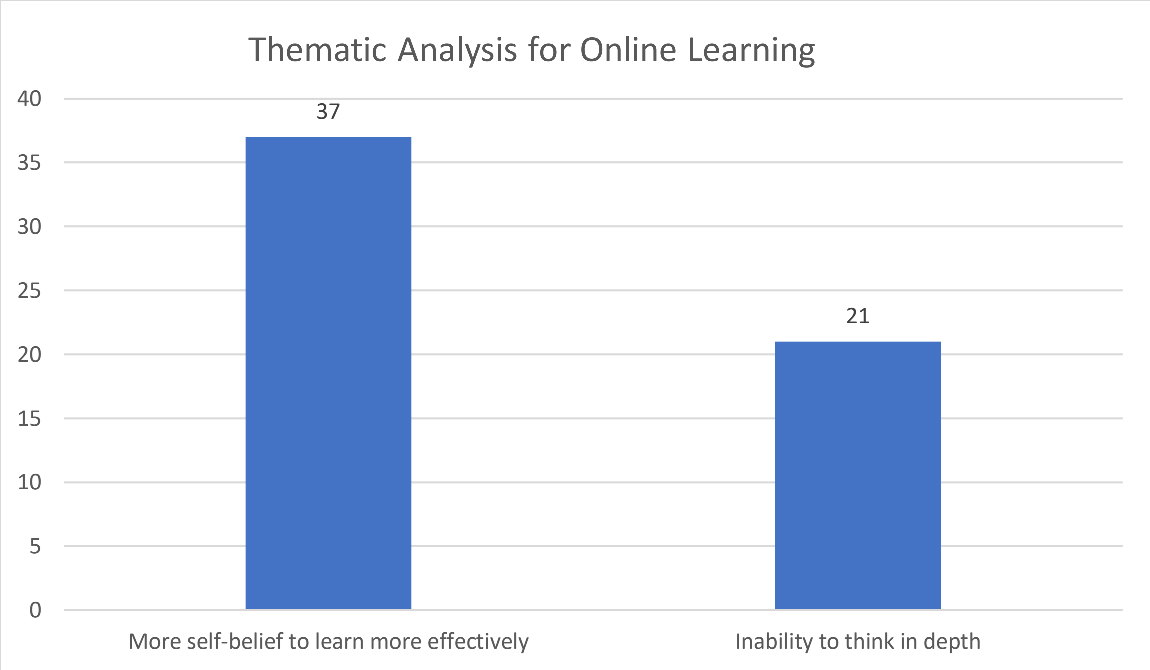

Figure 4.21: Thematic Analysis for Online Learning

This bar graph in Figure 4.25 provides a visual representation of the survey responses and helps identify the key themes or factors that the respondents considered significant when interacting with Msizibot for online learning.

From Figure 4.25 it can be seen that 37 of the respondents for this section were of the opinion that Msizibot provided an opportunity for them to become proficient users of the LMS without reliance on external help. The integrated assistance provided the students with a measure of self-belief in their capacity to navigate through the functionality of the LMS. On the other 21 of the respondents indicated that the responses provided by Msizibot to their requests for help, was not sufficient and quite superficial. This observation immediately prompted a perception that Msizibot will provide help that is limited and cannot be an adequate replacement for a human expert on LMS usage.

The results of the open-ended questions are encouraging because they suggest that, under the right circumstances, students may like using chatbots to support their academic activities because it mimics and aids them in online registration and learning. With such a good response from students, it is possible that the few opportunities for faculty and students to engage can be expanded, self-regulated learning can be ensured, and students can be exposed to unique learning cultures in which emerging technologies are used to support the faculty. Interacting with the chatbot can help students connect their coursework and real-world difficulties or precedents.

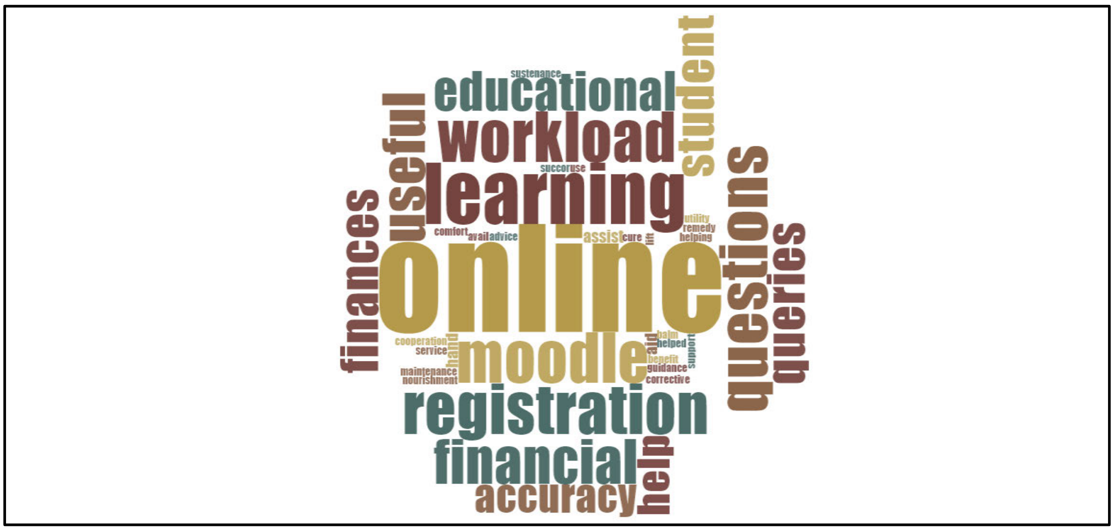

Figure 4.22: Word Cloud Generated by NVIVO

To improve the understandability of the results, a word frequency query was performed on the combined set of qualitative responses for online registration and online learning. From the word cloud illustration, it can be established that Msizibot provides a conduit to the topics of:

- Online learning via Moodle – help in educational matters pertaining to the University
- Online registration – a useful tool to provide accuracy with respect to the financial aspects of university registration systems and accuracy with module selection.

While this Word cloud did not make a major contribution to the overall thematic analysis, it provides an overview illustration of the main words used in the open-ended responses.

4.9 Chapter Summary

The findings of the research were reported in this chapter. The constructs of the UTAU model was used to drive the empirical data analysis presentation. The overall objective of the chapter was to provide the reader with an aggregated and statistically validated view of the study's raw data. The t-test was used to confirm the significance of the mean values that were reported suggesting that the aggregated values were a very good representation of the study's data. Pearson Correlation was used to establish a relationship between the study's independent and dependent variables and position the researcher to engage with a discussion that converges to the answering of the study's research questions. The qualitative data analysis provided the researcher with an opportunity to identify major themes that have emanated from this study so that an depth-driven insight into the use of the Msizibot tool for online registration and online learning could be obtained to provide an informed understanding to supplement the quantitative analysis

Chapter 5 – Summary, Conclusions and Recommendations

5.1 Introduction

This chapter presents a discussion of the research's findings, which were presented in the previous chapter, as well as the study's conclusion which will be contextualised according to the study's research questions that are re-presented here for ease of reference. The chapter also includes the researcher's suggestions that have been crafted from the empirical analysis on achieving greater impact in chatbot usage as well as suggestions on how th the technology may be improved from the perspectives of online registration and learning.

5.2 Summary of the study

This section discusses how the research questions have been answered and the objectives have been achieved.

The main objectives of the study are listed here for ease of reference:

The study aimed to identify factors that link user acceptance of the Msizibot (chatbot) at UKZN to support online registration and online learning.

The specific objectives of the study (aligned to the study's set of research questions) are listed as follows:

i. To determine students' **behavioural intention to use** a chatbot to assist with **online registration** at UKZN.

ii. To determine students' **behavioural intention** to use a chatbot to assist with **online learning** (at UKZN via the Learn2022 LMS).

iii. To leverage students' **experiential knowledge** of using the Msizibot at UKZN to provide support for online registration at UKZN, be used to identify factors that will contribute to greater adoption of chatbot technology to support academic online academic registration.

iv. To leverage students' **experiential knowledge** of using a chatbot for online learning to improve students' adoption of the Msizibot to facilitate online learning via the UKZN LMS.

The study comprised of 5 chapters. The first chapter of the study defined the research problem and objectives. It also detailed the study's theoretical foundation, research methodology, and study restrictions. Finally, it summarized each section of the study.

A literature review of chatbot applications and their uses has been provided in Chapter 2. Challenges to using educational chatbots were also examined, as were the factors influencing their adoption as a tool to enhance academic activity. The chapter concludes with a review of the literature on the theoretical frameworks of IT adoption and its applications to studies of chatbot adoption.

This study's data collection and analysis methodology was described in detail in Chapter 3 using the research onion framework (Saunders et al., 2016). It was noted in the study's methodology section that the study's fieldwork was conducted on the Westville and Pietermaritzburg campuses of the UKZN. Students aged 18 to 35 made up the core of the target demographic. The data was gathered using a survey method and respondents for the study was identified via purposeful sampling. SPSS v25 was used for data analysis (descriptive and inferential statistics). NVivo was used for the analysis of the open-ended questions that formed part of the study's questionnaire.

The descriptive and inferential data analyses were presented in Chapter 4. The overriding objective in Chapter 4 was to obtained an aggregated version of the study's raw data and to ensure that the aggregated results were statistically significant so that the study's conclusion was valid. Pearson Correlation was used at the main statistical test to provide the researcher with empirical evidence to craft a discussion of the results which is presented in the current chapter (Chapter 5).

5.3 Summary of findings

The main goal of the study was to ascertain student's perceptions and intention to accept and adopt the Msizibot chatbot technology that has been implemented at UKZN to assist with online registration and online learning. The UTAUT model was identified as the perfect fit as a theoretical model to operationalise the abstract concepts such as acceptance and adoption. The conceptual model provided a set of factors that normally define user acceptance of technology (validated in previous UTAUT-based studies) that have been used to provide structure to the study's questionnaire items that were administered to 232 users (students at UKZN).

The research results show that students' performance expectancy substantially affects their behavioural intention to engage with the Msizibot chatbot. This claim is corroborated by the empirical data that shows a significant positive response regarding the expected performance of Msizibot in enabling online registration and assisting with usage of the LMS for online learning. This suggests that students value the Msizibot's presence to provide much need assistance during online registration, thereby saving time and effort. This assistance is also highly valued when it comes to usage of Msizibot for online learning and for mastering the Learn platform. These results resonate with the outcome of a study by Mohd Rahim et al. (2022) who conducted their study by using the UTAUT2 model. UTAUT2 also contains the construct of PE and it was found in a higher education setting that students have a significant behavioural intention to adopt the chatbot assistance provided service-oriented activities such as online registration as well as academic activities such as online learning. Slepankova (2021) used a qualitative approach in a similar study and discovered PE as a significant theme. The overwhelming nature of the responses was that chatbot usage enabled better student performance in registration and online learning. However, there was also a cohort of students who indicated a preference for the "human version" to provide them with assistance in registration and online learning.

From an effort expectancy perspective, findings in this study indicate a significant positive attitude towards the effort required to use the Msizibot. These results are corroborated in Mohd Rahim et al. (2022) and Slepankova (2021). However, based on the qualitative (open-ended questions) responses in the current study, it becomes quite clear that there is a lot of room for improvement to the Msizibot interface because there is a lack of instruction in terms of how to get meaningful assistance from Msizibot. These concerns regarding the effectiveness of user interfaces for chatbot based systems, is also echoed by Sandu and Gide (2019) who make the suggestion that higher education instructional chatbots should prioritize user-friendliness so that there is greater student engagement with these systems.

Most respondents to the study said that the chatbot application was used because of peer influence, which is aligned to the Social Influence (SI) construct used in this study. A significant majority of the respondents did indicate that people who are important to them and whose opinions they value influence their use of the Msizibot (for example, the university staff, lecturers and fellow students). This is an important finding because previous research has indicated that chatbot systems have a more significant potential for adoption when people of social influence persuade students to adopt specific technology (Akinnuwesi et al., 2022; Morris, 2016). The SI construct also receives comprehensive endorsement in Slepankova (2021) who extend this influence beyond the classroom for Generation Z students who are easily influenced on social media platforms such as Facebook, Instagram and Whatsapp in terms of usage behaviour towards technology.

Based on the study's overall findings, a robust positive correlation exists between the UTAUT constructs and Msizibot usage for online registration and online learning. These results are consistent with previous studies by El-Halees and Salah (2018) and Jain et al. (2012), which suggest that any Information System (IS) with high utilization rates requires good acceptance for the system to be considered viable. Acceptability is crucial in enhancing the potential for improved system efficiency and overall user satisfaction. However, Pfaff and Krcmar (2018) propose that in the case of inexperienced users, there has to be great focus on the user interface so that it is highly interactive and responsive in an intelligent manner. The depth and quality of responses to student queries by Msizibot has been highlighted (qualitatively) as a possible reason that students do not engage with the technology more prominently.

It should be noted that in a study by Marchewka et al. (2007), who applied the UTAUT model to analyse student adoption of educational technologies, it was reported that there was no significant association between PE and BI to use these technologies The results from the current study contradict this finding.

Sandu and Gide (2019) used a modified UTAUT model to explain the spread of chatbots at Indian universities. A total of 57 responses were collected through a web-based survey sent to college students. This study supports several correlations proposed by Venkatesh et al. (2003), including the positive effects of performance expectancy (PE) and social influence (SI) on the behavioral intention (BI) to adopt chatbot technology.

Terblanche and Kidd (2022) conducted a study to ascertain usage patterns for chatbot technology in the context of a social media platform. This study also made use of the UTAUT model and the results reported concur with the results from the current study. However, in the Terblanche and Kidd (2022) study it was found that PE was the greatest predictor of a user's BI to adopt chatbot technology. This is slightly different in the current study where EE has been identified as the greatest predictor of students' intention to use chatbot technology for online registration.

5.4 Recommendations

Based on the findings of this study, the following have been recommended:

Based on the student's feedback in this study, Msizibot's user-friendliness and accessibility on the web are significant factors in the system's widespread adoption and use. In light of this, it is strongly recommended that chatbot application developers adhere to generally accepted standards for usability and accessibility in information systems. In addition, developers must consider the chatbots' interoperability with existing systems, which might be used again or expanded to include various universities (Booty & Ansell,2019). The application itself should have features and tools that aid the end-users (students) in accomplishing their goals.

Increasing the capacity of the institution's human resources department with professionals with the technical insights, expertise, capability, and interests to provide strategic leadership in higher education institutions is something that management should consider if they want to improve the chatbot implementation (Bloom et al., 2017). Concerns about chatbot adoption and utilization highlighted in this study could be mitigated with the help of educated individuals with a solid grasp of technology. Higher education administrators, for instance, can ensure that the right kind of technological infrastructure has been set up and that students are given ongoing instruction on accessing and using the Msizibot safely, efficiently, and effectively. Institutions should designate positions for technical support personnel to ensure that questions and problems with the Msizibot are promptly addressed. Management is urged to take a stand for Msizibot's implementation and continued use while encouraging creative thinking among their students. Students will be more receptive to using the Msizibot if they see this done.

The researcher contributes to literature by positively correlating between UTAUT constructs and Msizibot utilization. The study’s findings establish a strong positive correlation between the UTAUT constructs and the use of Msizibot for online registration and online learning. This contributes to the theoretical understanding of technology acceptance and user experience in the context of educational chatbots. Importance of acceptance and user experience, the study underscores the significance of user acceptance and positive user experiences in ensuring the viability, efficiency, and user satisfaction of systems like Msizibot. This contributes to the broader literature on technology adoption and usability. Confidence in AI for enhancing efficiency, the study findings also align with the notion that students have confidence in the ability of AI, such as chatbots, to enhance their efficiency in academic activities. This adds to the growing body of knowledge on the perception of AI in education..

Overall, this makes important theoretical contributions to the understanding of chatbot technology acceptance, user experience, and its impact on educational processes. It also highlights avenues for future research and acknowledges the complexities and limitations inherent in this field of study.

5.5 Delimitations and Future Research

Students from the University of KwaZulu-Natal in South Africa were used as participants in this study. Furthermore, as shown in the findings section, the respondents were youth (between 18 and 35, as defined by South Africa). This means that the results can only be extrapolated to the age group of young people. However, because "youth" might refer to various age groups depending on the context, caution should be exercised before generalizing the study's findings to the youth population. Since all participants were students at the University of KwaZulu-Natal, the study was limited to a sample of "educated" young people. Therefore, additional research should be undertaken to evaluate the adoption of chatbot applications that assist academic engagement for youths without pursuing a formal degree. The researcher did not look into whether or not gender, age, experience, or willingness to utilize had a role as moderators. Since this research was only conducted at one university, the results may not generalize to students at other institutions.

The study was also conducted in 2 of the 5 campuses of UKZN. This restriction was driven by logistical constraints which may have compromised the validity of the study. However, the sample used in the study could be deemed to be adequate as an exploratory venture into the topic pf chatbot usage at a tertiary educational institution. In subsequent studies, this initiative could be explored further by extending the study to all 5 campuses of UKZN and possibly to other tertiary institutions in South Africa where chatbot technology is used to assist with online registration and online learning.

Despite its limitations, this research is a stepping stone towards examining the adoption of chatbots that support academic activities in the South African environment and from the youth's perspective.

5.6 Significance/Contribution of Study

Despite the scarcity of existing literature on the usability of university chatbots within the South African context, the current study has important objectives. It aims to provide policymakers and software developers with a valuable set of guidelines that can inform the analysis, design, and improvement of future versions of higher education chatbot systems.

In the realm of task-oriented chatbots, the primary determinant of success is utility. When it comes to applications involving task-oriented chatbots, the paramount goal is to effectively address users' problems and facilitate their achievement of objectives. Delivering a positive chatbot user experience hinges on the ability to provide valuable assistanc. In nearly all instances of chatbot applications, accurately deciphering user intentions and furnishing appropriate responses is of utmost importance. Despite chatbots still being an evolving form of interactive technology, service providers must exercise caution to ensure that their chatbots not only align with their intended functions but are also perceived as highly beneficial and valuable by their user base.

Følstad (2020)'s insights align with the ideas presented in the study. Emphasizing the value of understanding user experiences with chatbots and acknowledges the challenges in doing so. Underscores the critical role of user reports in improving chatbot uptake among the general population. The research approach adopted in this study, which incorporates elements inspired by Følstad (2020)'s findings, exemplifies the practicality and benefits of gathering qualitative user reports to gain a richer understanding of the chatbot user experience.

Furthermore, this research endeavor is expected to contribute significantly to the academic community, potentially inspiring further research on the usability of various AI employed by the Department of Education and other governmental departments. Additionally, it is envisioned that this study will play a key role in increasing the adoption of the university chatbot system, ultimately leading to enhanced access to information and more informed decision-making within the education sector.

5.7 Conclusion

The study's findings, supported by the research of El-Halees and Salah (2018), Jain et al. (2012), and Pfaff and Krcmar (2018), reveal a strong positive correlation between the UTAUT constructs and the utilization of Msizibot for online registration and online learning. Acceptance and good user experience are crucial for system viability, efficiency, and user satisfaction. The findings of a study conducted by Chatterjee et al. (2020) align with the thesis on the acceptance of chatbot technology to support academic activity at the University of KwaZulu-Natal. The study reveals that students have confidence in the ability of AI to enhance their efficiency.

In line with this, the majority of respondents in a survey agreed that using the Msizibot improves their chances of successful registration, as supported by the findings of Efiloğlu Kurt and Tingöy (2017). Additionally, the study conducted by Avella et al. (2016) and Nassuora (2012) found that chatbot technology in education is seen as an innovative tool with the potential to enhance pedagogy and the overall educational experience.

This section summarized each section of the dissertation and presented the study's findings in light of whether or not the research goals had been attained. The researcher also included some suggestions for further research in this chapter. The study's shortcomings were discussed, and recommendations for further research in chatbot applications were provided.

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APPENDICES

APPENDIX 1: ETHICAL CLEARANCE LETTER

UNIVERSITY OF KWAZULU-NATAL™
INYUVESI YAKWAZULU-NATALI

25 November 2022

Ebunoluwa Ehikowoicho Johnson (218018217)
School Of Man Info Tech & Gov
Pietermaritzburg Campus

Dear EE Johnson,

Protocol reference number: HSSREC/00004979/2022
Project title: The acceptance of chatbot technology to support academic activity at the University of KwaZulu-Natal
Degree: Masters

Approval Notification – Expedited Application

This letter serves to notify you that your application received on 09 November 2022 in connection with the above, was reviewed by the Humanities and Social Sciences Research Ethics Committee (HSSREC) and the protocol has been granted **FULL APPROVAL**.

Any alteration/s to the approved research protocol i.e. Questionnaire/Interview Schedule, Informed Consent Form, Title of the Project, Location of the Study, Research Approach and Methods must be reviewed and approved through the amendment/modification prior to its implementation. In case you have further queries, please quote the above reference number. PLEASE NOTE: Research data should be securely stored in the discipline/department for a period of 5 years.

<u>This approval is valid until 25 November 2023.</u>
To ensure uninterrupted approval of this study beyond the approval expiry date, a progress report must be submitted to the Research Office on the appropriate form 2 - 3 months before the expiry date. A close-out report to be submitted when study is finished.

HSSREC is registered with the South African National Research Ethics Council (REC-040414-040).

Yours sincerely,

[redacted]

Professor Dipane Hlalele (Chair)

/dd

APPENDIX 2: INFORMED CONSENT

UKZN HUMANITIES AND SOCIAL SCIENCES RESEARCH ETHICS COMMITTEE (HSSREC)

APPLICATION FOR ETHICS APPROVAL
For research with human participants

Information Sheet and Consent to Participate in Research

Date: 28/10/2022

Greetings,

My name is Ebunoluwa Johnson (Student No. 218018217) and I am currently studying for a Master of Commerce (MCom) degree at the University of KwaZulu-Natal (UKZN), in the School of Management, Information Technology and Governance. The discipline of my study is in Information Technology (IT). The contact details for myself as well as my supervisor and the academic department at UKZN are listed below:

Researcher Name: Ebunoluwa Johnson; e-mail: 218018217@stu.ukzn.ac.za ;
Mobile Contact Number: +27 (62) 366 9914
Supervisor Name: Dr. S Ranjeeth email: ranjeeths@ukzn.ac.za
Office contact Number: +27 33 260 5641
Department of Information Systems & Technology: +27 33 260 5704; + 27 31 260 7051

You are being invited to consider participating in a study that involves research to identify factors that influence user acceptance of the Msizibot at the University of KwaZulu Natal (UKZN) to support online registration and online learning. The title of my study is:

The acceptance of chatbot technology to support academic activity at the University of KwaZulu-Natal

This study aims to identify the factors that influence the acceptance of chatbot technology at UKZN, to improve online student registration and online learning. The purpose of this research is to identify the barriers to implementing chatbot technology in universities with the goal of better serving their students. Given the numerous obstacles to implementing and approving AI applications in South Africa, the study is extremely vital to the local context. Your participation in the study will require you to respond to survey-based questions regarding your opinion of the UKZN Msizibot and to provide an account of the knowledge you have gained through using the UKZN Msizibot. The responses will be analyzed for trends to help a researcher determine how chatbot technology will be used to enhance the registration and online learning processes for students at the University of KwaZulu-Natal.

It is anticipated that your participation will take no more than 15–20 minutes of your time.

In the event of any problems or concerns/questions you may contact the researcher by making use of any of the contact details provided above, or by contacting the UKZN Humanities & Social Sciences Research Ethics Committee. The contact details are as follows:

HUMANITIES & SOCIAL SCIENCES RESEARCH ETHICS ADMINISTRATION
Research Office, Westville Campus
Govan Mbeki Building
Private Bag X 54001
Durban 4000 KwaZulu-Natal, SOUTH AFRICA
Tel: 27 31 2604557- Fax: 27 31 2604609
Email: HSSREC@ukzn.ac.za

Your participation in the study is voluntary and by participating, you are granting the researcher permission to use your responses. You may refuse to participate or withdraw from the study at any time with no negative consequence. There will be no monetary gain from participating in the study. Your anonymity will be maintained by the researcher and the School of Management, I.T. & Governance and your responses will not be used for any purposes outside of this study.
All data, both electronic and hard copy, will be securely stored during the study and archived for 5 years. After this time, all data will be destroyed. If you have any questions or concerns about participating in the study, please contact me or my research supervisor at the numbers listed above.

Sincerely

[redacted]

Ebunoluwa Johnson

CONSENT TO PARTICIPATE

I ………………………………………………………………………………………… (Name) have been informed about the study entitled *The acceptance of chatbot technology to support academic activity at the University of KwaZulu Natal* by Ebunoluwa Johnson.
I understand the purpose and procedures of the study. I have been given an opportunity to ask questions about the study and have had answers to my satisfaction. I declare that my participation in this study is entirely voluntary and that I may withdraw at any time without affecting any of the benefits that I usually am entitled to.
If I have any further questions/concerns or queries related to the study I understand that I may contact the researcher at the details provided in Page 1 of this document. If I have any questions or concerns about my rights as a study participant, or if I am concerned about an aspect of the study or the researchers then I may contact:

HUMANITIES & SOCIAL SCIENCES RESEARCH ETHICS ADMINISTRATION
Research Office, Westville Campus
Govan Mbeki Building
Private Bag X 54001
Durban
4000

APPENDIX 3: QUESTIONNAIRE

SECTION A: Demographic Information

Please select the option that would best fit your response by making a tick (✓) in the box provided and fill in required information

Part 1:

College:		
School:		
Gender:	Male	Female
Degree:		
Year:		
Age:		

Part 2:

How many ***years of experience*** *do you have in using a computer. Please tick (✓) the relevant cell).*

Number of years using a computer	Please Tick Appropriate box (✓)
0 – 2 Years	
3 – 5 Years	
6 – 10 Years	
11 – 15 Years	
16 Years +	

SECTION B: UTAUT Constructs

Part 1: Online Registration

Please select the option that would best fit your motivation style by making a tick (✓) in the box provided.

Construct	Description	**1** represents ***Strongly Disagree*** and **5** represents ***Strongly Agree***				
		1	**2**	**3**	**4**	**5**
Performance Expectancy (Registration)	I find the Mzibot useful during online registration					
	Using the Mzisibot increases my chances of achieving my online registration goals					
	Using the Msizibot helps me to complete my online registration quickly					
	Using the Msizibot increases my online registration productivity.					
Effort Expectancy	Learning how to use the Msizibot is easy for me during online registration.					
	My interaction with the Msizibot is clear and understandable for online registration.					
	I find the Msizibot easy to use for online registration.					
	It is easy for me to become skillful at using the Msizibot for online registration.					
Social Influence	People who are important to me think that I should use the Msizibot for online registration.					

	People who influence my behavior think that I should use the Msizibot for online registration.					
	People whose opinions that I value prefer that I use the Msizibot for online registration.					
Behavioural Intention	I intend to continue using the Msizibot for online registration in the future.					
	I plan to continue to use the Msizbot frequently for online registration.					

Part 2: Online Learning

Please select the option that would best fit your motivation style by making a tick (✓) in the box provided.

Construct	**Description**	**1** represents ***Strongly Disagree*** and **5** represents ***Strongly Agree***				
		1	**2**	**3**	**4**	**5**
Performance Expectancy (Online Learning)	I find the Mzibot useful during online learning.					
	Using the Mzisibot increases my chances of achieving my online learning goals.					
	Using the Msizibot helps me to complete my online learning quickly					
	Using the Msizibot increases my online learning productivity.					
Effort	Learning how to use the Msizibot is easy for me during online learning.					

Expectancy	My interaction with the Msizibot is clear and understandable during online learning.					
	I find the Msizibot easy to use for online learning.					
	It is easy for me to become skillful at using the Msizibot for online learning.					
Social Influence	People who are important to me think that I should use the Msizibot for online learning.					
	People who influence my behaviour think that I should use the Msizibot for online learning.					
	People whose opinions that I value preferthat I use the Msizibot for online learning.					
Behavioural Intention	I intend to continue using the Msizibot for online learning in the future.					
	I plan to continue to use the Msizbot frequently for online learning.					

SECTION C – Open-ended Questions

Please describe your experience with the Msizibot chatbot from the University of KwaZulu Natalin an open-ended manner that reveals your overall impression of the chatbot.

1. What can you tell us about your experience of using the Msizibot chatbot facility provided by UKZN. Please comment of the effectiveness and the user experience of using this facility.

2. Was the Msizibot able to help you attain the objectives you had set? Was the chatbot able to help you with your registration and online learning questions? If not, what can be done to make it better?

Thank you for your response!