Exploration of the adoption of Artificial Intelligence within traditional recruitment and selection processes among South African Universities

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DECLARATION

I, Godwin Murerwa, declare that this consultancy report is my own work except as indicated in the references and acknowledgements. It is submitted in partial fulfilment of the requirements for the degree of Master of Business Administration in the Graduate School of Business Administration, University of the Witwatersrand, Johannesburg. It has not been submitted before for any degree or examination in this or any other university

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Signed at: Johannesburg

On the 30th day of June 2023

ABSTRACT

Industries across the world are investing in and embracing artificial intelligence in their recruitment and selection strategies. Artificial Intelligence (AI) in talent acquisition, fuelled through technological innovation has disrupted traditional recruitment and selection processes. Within South Africa, adoption of AI has been reported to be slow with most organisations still at a pilot stage. An organisation competitive advantage is generated from the people it employs. Due to increased globalisation and interlinked economies, companies rely on their highly talented employees for sustainable competitiveness. It is critical in a world where there is scarcity of skills, talent and resources to use an intelligent system in staffing. Traditional techniques of managing entities are being contested globally. Traditionally, recruitment and selection was a laboriously administrative, mundane and manual process susceptible to prejudices and biases of the practitioner.

This research explored the factors influencing Artificial Intelligence adoption in the traditional recruitment and selection practices among South African universities. The main objectives of the study were to establish factors influencing the adoption of Artificial Intelligence in recruitment and selection processes among South African universities and consequently recommend feasible strategies of adopting such technology within the talent acquisition practices of the universities.

The study utilised a quantitative research approach through a survey design. For data collection, the research instrument was an online self-completion questionnaire. The study employed non-probability sampling, purposive sampling in particular. This enabled the research to focus on the characteristics and attributes consistent with the study objectives. A total of ninety-five participants from nine South African universities completed the online questionnaire.

The findings demonstrated the potential benefits of AI adoption to the hiring processes of South African universities. The benefits of AI adoption seem to be mostly in perceived accuracy and speed in which it curtails tedious tasks in recruitment and selection. There are however significant challenges that should be addressed. Issues to do with ethics,

security and privacy concerns, the training or readiness of human resources practitioners in technology adoption and potential pitfalls of AI algorithms in recruitment will require new policy regulations and strategies to address such challenges. Additional research is necessary in exploring such probable AI adoption advantages and limitations in different contexts and to develop strategies that enhance AI adoption in recruitment and selection.

The study helps in the discernment of the factors that influences adoption of artificial intelligence within traditional recruitment and selection practices of South African universities where literature is scant. This research, especially done within the South African context, will bridge such knowledge gap. The study will benefit Universities and other institutions aiming to replace their traditional recruitment and selection technology or integrate elements of artificial intelligence in their staffing processes, as it provides a basis for possible artificial intelligence adoption strategies, enabling improved talent sourcing policies and hiring practice efficiency.

Keywords: artificial intelligence, recruitment and selection, adoption, technology organisation and environment model (TOE)

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DEFINITION OF KEY TERMS AND CONCEPTS

Words / Phrase in Title	**Meaning According to academic articles**
Technology Adoption	Is defined by Hall and Khan (2003, p.1) as 'the choice to acquire and use a new invention or innovation'.
Artificial-Intelligence	A computer system imitation of human intelligent processes, simulating the "problem-solving and decision-making capabilities of the human mind" (IBM Cloud Education, 2020)
Traditional Recruitment and Selection Processes	Candidate or talent sourcing or attraction mostly through advertisements, referrals or employer branding; manual screening CV screening; assessing through face-to-face interviews, background verifications and hiring the best candidate (Vanderbist, 2020, p.5)

ABBREVIATIONS

Acronym	Description
ADP	Adoption
AI	Artificial Intelligence
AGI	Artificial General Intelligence
ANI	Artificial Narrow Intelligence
ASI	Artificial Superintelligence
CHE	Council on Higher Education
COM	Competitive Pressure
COS	Cost Effectiveness
DOI	Diffusion of Innovation Theory
HRR	Human Resources Readiness
PLS-SEM	Partial Least Squares-Structural Equating Modelling
POPI	Protection of Personal Information Act 2013
REA	Relative Advantage
RS	Recruitment and Selection
SAQA	South African Qualifications Authority
SEM	Structural Equating Modelling
SFG	Support from Government
SNP	Security and Privacy Concerns
SPSS	Statistical Package for Social Sciences
STV	Support from AI Vendors
TAM	Technology Acceptance Model
TAM 2	Technology Acceptance Model 2
TMS	Top Management Support
TOE	Technology Organisation and Environment
UTAUT	Unified Theory of Acceptance and Use of Technology

CHAPTER 1: RESEARCH INTRODUCTION

This research provides an exploration of the adoption of artificial intelligence within the traditional recruitment and selection processes among South African universities. The first chapter provides the research introduction. Part 1.1 is an introduction to the study background and context. In Part 1.2 the research is contextualized firstly through Section 1.2.1 the Problem Statement, Section 1.2.2 Research Aim, Section 1.2.3 Research Objective, Section 1.2.4 Research Question and hypotheses. 1.3 Research Scope, Section 1.4 provides the delimitations and assumptions of the research while; 1.5 examines the significance of the research with 1.6 providing the preface of the research.

1.1. Study Background and Context

Continued digital technological innovation and transformation has brought Artificial Intelligence to the fore. Artificial Intelligence (AI) being defined among other scholarly definitions, as a computer system imitation of human intelligent processes, simulating the problem-solving and decision-making capabilities of the human mind (IBM Cloud Education, 2020). Artificial intelligence as Maheshwari (2023) puts it, is a representative of a computerised machine with human-level intelligence, loaded with diverse cognitive competencies specifically programmed to perform assorted tasks. Used to build intelligent machines, AI incorporates a number of features and proficiencies (Bhatt, 2022). These capabilities continue to shape and enable many industrial sectors with increased adoption in business processes including traditional recruitment and selection practices. Rodney, Valaskova and Durana (2019) have noted the escalation in the adoption of AI in organisations also demonstrable by the proliferation of a number of publications that have continued to grow in recent years.

Johansson and Herranen (2019) have observed a shift in scholarly thinking from studies focusing on how technology could improve and streamline the recruitment process to current discussions on the adoption of technology for increased automation to support human resources professionals. The conclusion drawn is that ‘the human touch’ is being lessened due to technological adoption (Johansson & Herranen, 2019). With continued

innovation, todays' organisations are increasingly competing internationally, increasing the need for high calibre talent (Bai & Dixit, 2016). Competing for talented employees will require cost effective yet first-rate recruitment and selection systems that will enable organisations to gain sustainable competitive advantages. The prognosis of traditional talent acquisition practices according to Johansson and Herranen (2019), is of a prolonged, time-consuming, paper based and manual process.

With AI adoption, the future world of work has been brought forward (Kaur, 2021). According to the World Economic Forum (2020) the lockdown measures imposed due to the Covid-19 pandemic resulted in an increased adoption of technology. They anticipate that by 2025, the balance of task integration performed between humans and machines in the workplace will be uniform (The World Economic Forum, 2020). The future labour marketplace will see worker displacement due to automation and augmentation (The World Economic Forum, 2020). Universities should thus better prepare as there would be emerging and declining jobs and skills with the future demanding scarce new skills (The World Economic Forum, 2020). For sustainability, organisations will need effective recruitment strategies that embrace technological advancement. Kaur (2021) recognises the impact of the Covid-19 pandemic, which accelerated the adoption of new technological transformation beyond what was initially projected to befall by 2030. Kaur (2021) firmly believes that AI will revolutionise the hiring process and fundamentally transform the composition of the workforce.

Várallyai, Fraij and Laszlo (2021) have observed the swift transformation occurring within the business landscape, posing significant challenges for human resources departments as they navigate an unprecedented and inevitable new paradigm. Traditional recruitment and selection processes which relied on the skills and capabilities of individual human resource practitioners are now judged inadequate in the face of a changing labour market whose emerging jobs make the use of technology in recruitment indispensable. Várallyai *et al.,* (2021) believe the world over, organisations are in an escalating need to find talented and multiskilled candidates who can compete in the global market. The burdensome task of manually screening job applications has also been shown to be liable

to prejudice and bias. Reducing human errors entail improved accurateness and precision in a decision outcome, this according to Maheshwari (2023), is one of the advantages of AI adoption due to decision 'based on systems on past data' and relevant programmed algorithms. Upadhyay and Khandelwal (2018) believe artificial intelligence is disrupting the recruiting industry. Its powered systems are taking and making obsolete the mundane, repetitive tasks traditionally performed by humans (Upadhyay & Khandelwal, 2018). The systems are always at one's disposal 'around the clock', not taking a break like their human counterparts yet accurately performing dreary and cyclic duties effortlessly (Maheshwari, 2023). Adoption of artificial intelligence will enable better recruitment and selection outcomes, reducing reliance on human resource in the process.

There is a worldwide transition from conventional recruitment and selection methods towards the utilisation of AI-powered capabilities aimed at enhancing the efficiency and effectiveness of hiring operations (Kumaraswamy, 2022). An example of this shift is the application of artificial intelligence, specifically through the use of data and predictive analytics, which enables the prediction of a candidate's potential for success in a specific job position (Várallyai *et al.,* 2021). Through traditional recruitment, a recruiters' unconscious stereotyping might preclude an objective assessment of the candidate's skills and capabilities. Most companies therefore have "enrolled" this innovation baring talent that had been typically overlooked (Várallyai *et al*., 2021). In the case of Google, through their qDroid internal recruitment application, candidate background which would have been a source of bias were disregarded (Várallyai *et al.,* 2021). Artificial Intelligence enabled applications can allow candidate assessment before the interview process. Such an analysis can be concluded against a uniform baseline score and ranked accordingly, resulting in an attractive talent pool (Ahuja, 2020).

O'Donovan (2019) and Galanaki *et al*. (2019) highlighted the role of technological innovation in enabling the advancement of talent acquisition practices towards being more streamlined and optimised. Ahuja (2020) provides candidate sourcing, screening, engagement and assessment as broad categories of artificial intelligence use in recruitment. Bhatt (2022) adds 'final selection' to the categories.

Empirical research adding to theoretical understanding on artificial intelligence adoption within South Africa businesses is limited. According to Moyo (2019), South Africa's overall decade long investment into artificial intelligence amounted to USD 1.6 billion. Top use of the innovation was reported as 83% automation while 70% was in prediction Moyo (2019). Interestingly Moyo (2019) highlights that South Africa's unemployment rates are high whilst the appreciation of artificial intelligence is low, any form of automation eagerness, is quickly extinguished by apprehension of job losses. At present most entities still need diverse core AI competencies to enable AI maturity (Moyo, 2019). Moyo (2019) notes that 46% of South African companies are in the pilot stages of artificial intelligence implementation while 54% 'rate the impact on personnel as' a leading commercial risk of adoption. Le Roux (2018) informs in 'the past two centuries, the job-creation effect of technological progress has counter-balanced its job-destruction effect' at least in 'healthy economies,' citing Brynjolfsson and McAfee (2012). Evaluating likely dominant factors that hinder or promote adoption of AI is imperative. However, this may not be the case for a developing economy like South Africa. In fact, technology may in essence result in job displacement, a genuine concern within an ailing economy. There is likely therefore to be 'human resistance' due to a genuine fear of losing jobs (Moyo, 2019).

South African itself has a paradox of high levels of unemployment and a lack of critical skills which affects its growth and development. Unemployment is pegged at 35,3% representing 7,9 million jobless persons as per the fourth quarter of 2021 (Stats SA, 2022). In February 2022, the South African Department of Home Affairs published a critical skills list of diverse competencies needed in South Africa (Businesstech, 2019). Among these, the country in general and universities in particular needed highly qualified and competent academics. Deductions can be drawn that the labour market pool for South African Universities is therefore characterised by scarcity of qualified candidates as well as abundance of unqualified applicants depending on the job requirements. Artificial Intelligence adoption can assist in the identification of high calibre talent that are less likely to actively apply for opportunities and may be difficult to notice in the job market.

The best talent might be passive to active job search, and artificial intelligence affords, through automated marketing, an ‘efficient and effective’ way to proactively reach a wider candidate pool (Ahuja, 2020). Checkr (2019) gives an example of Royal Dutch Shell, who used machine learning through the Shell Opportunity Hub, to match internal talent to organisational needs. With successive utilisation of machine learning, artificial intelligence was further refined, enabling even better matches. Department of Higher Education and Training (2019) observed continued reports of racism within SA universities where among others insinuations are that persons ‘were recruited for demographic rather than academic reasons’. As in the case of Royal Dutch Shell, use of artificial intelligence powered applications can objectively enable human resources to create a talent pool even for succession, consider external applications and diversity management through use of algorithm enabled ‘talent analytics’ which cross check requisite skill sets.

Universities themselves do not exist in a talent market vacuum. The changing world of work, will demand a paradigm shift based on transformative technologies like artificial intelligence. To attain their diverse objectives, universities need talent with requisite competencies and capabilities. Such talent can be attainable through intelligent recruitment, through artificial intelligence adoption. Finding the right talent is critical given the mirrored challenges within universities including the “quality of teaching and learning” which affects student throughput and considering the global rise in studentship (Fomunyam, 2018). Literature, although scant, is available on adoption of artificial intelligence in resolving higher education challenges. In the case of India for instance, Chatterjee and Bhattacharjee (2020) notes that the workload due to massification of students is increasing and thus, for example, propose use of the technology in optimising learning. Within South Africa, Fomunyam (2018) quotes Cloete (2016) who indicated that between 2006 and 2013, student numbers in higher education grew by 194,000. This growing demand, according to Fomunyam (2018) has generally increased pressure on universities to deliver at an optimal level.

1.2. Research Conceptualisation

1.2.1. Problem Statement

According to Rozario, Venkatraman and Abbas (2019), organisations are more concerned about how they attract their most valuable asset - the human resource - in a highly competitive global environment. To make this crucial decision, they need to have a process that is as close to flawless as possible. However, the traditional recruitment and selection processes that rely on human resources personnel to advertise through newspapers, costly recruitment agencies and job boards and to screen manually hundreds of job applications with possible bias and subjectivity are not very effective in finding the best candidates. Chen (2022) argued that traditional talent sourcing is inefficient because it takes too long and does not source high quality talent consistently. CVVIZ.com (2022) also reported that 73% of employers face difficulties in finding skilled employees. In traditional recruitment and selection processes, human resources practitioners have to perform the tedious and boring task of finding the needle in the haystack, which may lead to inaccurate and subjective candidate screening. Traditional recruitment uses less sophisticated methods like print media adverts or referrals from existing employees to attract candidates (Chen, 2022).

Ahuja (2020) and Kaur (2021) both highlighted the significant role of artificial intelligence in the domain of talent sourcing, where it can enable the analysis of massive amounts of data in order to swiftly pinpoint the most suitable and talented candidates from a vast and diverse pool of talent. The quality of the data that is fed into the AI algorithm is a crucial factor that determines the level of impartiality, precision, accuracy and speed that the algorithm can achieve in sifting through the data points of various candidates, thereby reducing the time required to recruit by quickly identifying the candidates who have the potential and qualifications that match the job requirements (Kaur, 2021). Kaur (2021) also cited the example of Vodafone, which had successfully leveraged artificial intelligence to screen more than 100,000 applicants for only 1,000 vacancies. In a similar vein, Checkr (2019) reported that L'Oréal received an overwhelming number of job applications on its website, with more than five million visits per year. To streamline the

screening process, eliminate irrelevant applications and select excellent candidates, they employed AI to gain insights into the candidates' profiles, which resulted in an impressive 82% increase in the placement ratio of candidates who were interviewed and hired, as well as an improved career trajectory for the hired candidates once they joined the company (Checkr, 2019).

The current labour market poses a relative challenge for sourcing talent, and universities are not exempt from this situation. It is a formidable and costly endeavour to search for scarce skilled employees, especially highly accomplished academics, and it is becoming more difficult as time goes by. Nevertheless, it is essential to acknowledge that contemporary recruitment practices, such as the participation of search committees, the utilisation of extensive networks of academics both locally and globally, can facilitate talent scouting. Sometimes the real challenge is not in finding potential talent, but in the capacity of universities, particularly in South Africa, to attract and retain such talent. The inherent difficulty stems from the fact that South African universities may not have the same level of appeal and incentives as their counterparts in the global north, requiring a nuanced comprehension of the intricate dynamics involved in talent acquisition. In general, the employment of search committees with the assistance of AI can help identify exceptional talent, but to maintain a competitive edge, universities need positive hygiene and motivation factors to enable talent attraction and retention. Talent sourcing has also transformed from the conventional print media advertisements to more accessible social recruitment networks like LinkedIn, which has enabled extensive networking. Suitability screening does not have to wait for a search committee, but rather be integrated in a technology that enables talent sourcing, succession planning and exit management talent system. Print advertising, as is the case in traditional recruitment, does not necessarily reach most candidates, especially those passive to the job market. According to CVVIZ.com (2022), ‘more than 70% of workforce is a passive talent’, harder to find when relying on traditional recruiting practices. Among others, AI enabled job matching may permit quick and accurate matching of prospective yet passive talent.

Candidate screening is very crucial in recruitment and selection processes. It involves matching the personnel specifications in qualifications, experience and other attributes

including behavioural, to the vacancy. With huge unemployment currently experienced in South Africa, job advertisements are likely to attract hundreds of applications. Traditional recruitment and selection practices would entail manual drafting a schedule and use of weightings to shortlist candidates, although such screening is seemingly easy and effective, AI has the advantage in this early stage of the recruitment exercise by especially giving due consideration to excellent candidates who otherwise may fall through the cracks and their applications erroneously disregarded by the manual process.

Diversity management especially through recruitment, has been a thorn in the flesh for some universities, with persistent allegations of racism and perceived unmerited employment equity recruitment (Department of Higher Education and Training, 2019). While AI has the potential to reduce human bias in decision making, it is not immune to bias itself. Bias can arise from various sources, such as the data used to train the algorithms, the design and implementation of the algorithms, and the context and interpretation of the algorithmic outputs. Therefore, it is important to be aware of these sources and to adopt a socio-technical approach that considers the larger social context in which AI operates. For example, some ways to address bias in AI include creating diverse and inclusive teams that can reflect different perspectives and detect bias in the data and the output, applying rigorous testing and evaluation methods to ensure fairness and accuracy, and engaging with stakeholders and users to ensure transparency and accountability. By doing so, AI can become a more reliable and responsible tool for making better employment decisions based on merit and performance.

It is critical to conduct a study where literature is currently insufficient, to appreciate how adoption of AI technologies can be done through variable analysis of factors that may influence such adoption. AI-based applications have numerous benefits in talent sourcing, automated screening, candidate interviews through chatbots, assessments, background checks and predictive analysis which can aid impartial diversity management.

1.2.2. Research Aim

The purpose of the study was to understand the factors that influence artificial intelligence adoption in recruitment and selection processes within South African universities,

exploring TOE constructs as variables that may influence such adoption. After data analysis, generated insights influenced strategies for artificial intelligence enabled recruitment and selection. The study also provided a basis for literature within a South African context.

1.2.3. Research Objectives

a) To determine factors that influence the adoption of artificial intelligence in recruitment and selection processes among South African universities?
b) To determine if cost effectiveness of artificial intelligence for recruitment and selection influence the adoption of artificial intelligence for recruitment and selection of South African universities.
c) To establish if relative advantage of artificial intelligence for recruitment and selection influence the adoption of artificial intelligence for recruitment and selection of South African universities.

1.2.4. Research Questions

RQ1: What factors influence the adoption of artificial intelligence in recruitment and selection processes among South African universities?

RQ2: What is the relationship between the cost effectiveness of artificial intelligence for recruitment and selection and the adoption of artificial intelligence for recruitment and selection?

RQ3: Does the relative advantage of artificial intelligence for recruitment and selection affect the adoption of artificial intelligence for recruitment and selection?

RQ4: What strategies can be considered to enhance adoption of artificial intelligence in recruitment and selection among South African universities?

1.3. Research Scope

The study is confined within the Technology Organisation and Environment model and aligned conceptual framework, in assessing the factors influencing artificial intelligence adoption within the human resource function of recruitment and selection in the context

of South African universities. In the world of Artificial Intelligence complexity, the scope of the study was limited to Artificial Narrow Intelligence or ANI also referred to as Weak artificial intelligence.

1.4. Study Limitations and Delimitations

Limitations in a research study refer to the inherent constraints or shortcomings that could impact the generalisability or validity of its findings. These limitations are usually beyond the control of the researcher. For example, in this study, the generalisability of the findings was compromised due to a low response rate; only 95 of the 144 targeted participants completed the survey. This also raised concerns about a potential non-response bias, which might have further affected the study's validity. Moreover, legal constraints from the Protection of Personal Information (POPI) Act limited the avenues through which the researcher could reach potential participants. This not only restricted the sample size but also raised questions about the representativeness of the sample, as it necessitated making an assumption that the respondents were indeed from the field of human resources. Finally, the study could not control for all variables that might influence the adoption of AI, leaving some questions about the study's external validity.

On the other side, delimitations are those boundaries intentionally set by the researcher to define the scope and focus of the study. These delimitations can help to provide insights into the study's robustness and its applicability to broader contexts. In this case, the research was designed to scrutinise the influence of the Technology, Organization, and Environment (TOE) framework on AI adoption, thus limiting its application to other possible frameworks or theories. While individual behavioural and perceptual factors might influence AI adoption, these were deliberately excluded to maintain the study's focus on organisational-level factors. Similarly, though the study acknowledged that respondents might differ in terms of their hierarchical positions, job titles, educational backgrounds, and levels of computer literacy, it did not consider these factors significant within its chosen framework. The study was also specific in its operational scope, focusing exclusively on the field of human resource management, thereby limiting its applicability to other sectors or organisational roles.

By articulating these limitations and delimitations, the study aims to offer a nuanced understanding of its boundaries, thereby indicating areas for potential improvement and future research. It also serves to clarify the specific framework and focus that guided the investigation.

1.5. Significance of the Research

According to Shivdasani (2019), there has been extensive discussion about recruitment automation for several years, but its widespread adoption has not yet occurred. There has been minimal progress in implementing automation specifically in the areas of talent sourcing, screening, and assessing. Shivdasani (2019) notes that recruitment processes continue to rely on paper-based, manual methods, which are often tedious and involve repetitive and administratively burdensome tasks. However, there is a glimmer of hope as the market reception of automated candidate sourcing and screening, albeit slow, continues to persist. This suggests that there is potential for improvement and advancement in the adoption of automation within recruitment practices. Universities, the AI vendors, regulatory bodies and other such organisations or entities may not only improve understanding of critical imperatives within AI adoption but enable aligning tailored technology adoption strategies. The Department of Higher Education may for instance draft policy frameworks aligned to AI adoption, critical for regulating recruitment practices especially giving due regard to ethical considerations, security and privacy concerns when using the technology.

The research contributes to the understanding of artificial intelligence and espouse practical adoption opportunities in support of this critical business process. Resultantly, entities would be able to streamline recruitment and selection processes that will help limit prejudice and bias, enhance accuracy and speed while aiding diversity management and reducing employment costs.

Empirical research on artificial intelligence adoption within recruitment and selection among South African universities is at most non-existent. This research could facilitate additional studies focussed on artificial intelligence uptake in the recruitment and selection process and enhance literature. This study can expand the knowledge of AI

adoption in the talent acquisition process within a South African context in general and within South African universities in particular. It adds to the technological adoption theory thus improving on the scant literature.

In light of the complexities of the future world of work, the study will provide Universities in South Africa a practical basis for aligned human resources strategies, permitting AI adoption for sustainable competitive advantages through better talent sourcing and screening mechanisms as conferred by AI and its continued development.

1.6. Report Preface

This research report is comprised of 5 chapters. The first chapter has provided the introduction. Chapter 2 reviews the literature, provides definitions and conceptual issues, hypotheses development, theoretical frameworks in technological adoption and the conceptual framework. Chapter 3 provides the research approach, design, sampling and data collection, analysis and processing methodology, validity and reliability measures and ethical considerations. Chapter 4 incapsulates the analysis and presentation of the research results including reliability tests and statistical analysis. Chapter 5 concludes with summary and implications of the findings, limitations and future research, recommendations and conclusion.

CHAPTER 2: LITERATURE REVIEW & CONCEPTUAL FRAMEWORK

This section provides an in-depth understanding of the research problem, identifying the knowledge gap and introducing the theoretical framework of technological adoption that was used for the analysis of the research findings. Definitions and Conceptual issues were covered in Section 2.1, while Section 2.2 reviews literature and the development of hypotheses. Section 2.3 details theoretical frameworks in technological adoption, leading naturally to the TOE imbued conceptual framework in Section 2.4.

2.1. Definitions and Conceptual Issues

Artificial Intelligence (AI)

Several definitions exist in literature for Artificial Intelligence. Artificial Intelligence can be defined as the utilisation of digital technology to develop systems that are capable of independently performing tasks that are typically associated with human intelligence (Charlwood and Guenole, 2022).

In dissecting the evolution of Artificial Intelligence, Petersson (2023) lists four main types of AI as denoted in Figure 2.1. These are Reactive AI; which has memory but merely responds to different stimuli, Limited memory machines AI; which utilises memory to study and develop responses, Theory of mind AI; which comprehends the requirements of other intelligent objects or beings and Self-aware AI; which is human-like intellect and self-conscious (Joshi, 2019).

Reactive AI and Limited memory machines AI are classified as narrow AI as they are competent to accomplish narrow range of tasks. Theory of mind AI and Self-aware AI are often referred to as strong AI and are still to be attained (Petersson, 2023).

Figure 2.1: Four main types of artificial intelligence: The evolution of AI.

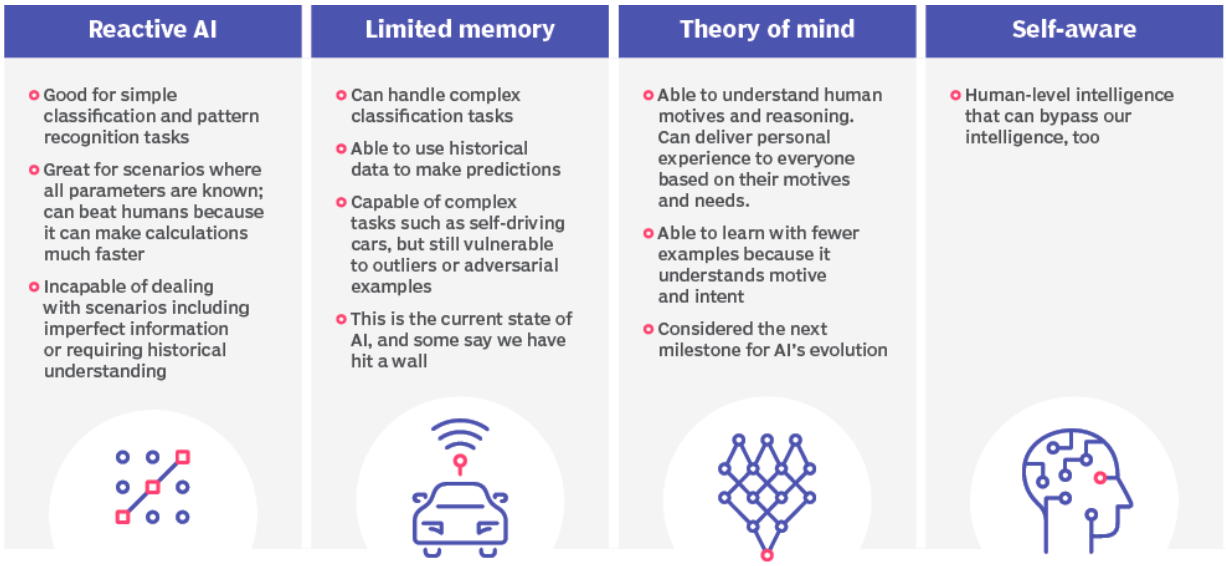

Figure 2.1: Four Main Types of Artificial Intelligence: The evolution of AI. Adopted from Petersson, 2023

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Within the technology industry, Joshi (2019), highlights the common general three categorization of Artificial Intelligence in order from simplicity to complexity into 'Artificial Narrow Intelligence (ANI), Artificial General Intelligence (AGI), and Artificial Superintelligence (ASI). Artificial Narrow Intelligence (ANW) is representative of all existing AI formed to date in its simplest and even complex forms (Joshi, 2019). It is AI that merely executes a task independently through human-like competencies. Petersson (2023) describes Artificial General Intelligence (AGI) as often understood to be 'strong AI', it is unrealised multidimensional machine intellect with the similar learning and understanding as humans. Artificial Superintelligence (ASI) has not been attained (Joshi, (2019). It is the self-awareness and marked intellectual competencies beyond human attainment (Petersson, 2023). Accordingly, this research's reference to Artificial Intelligence (AI) implies Artificial Narrow Intelligence.

Pillai and Sivathanu (2020) cite Charlier and Kloppnburg, (2017) who informed that within human resources AI is said to be functioning at three levels which are Assisted Intelligence, Augmented Intelligence and Autonomous Intelligence. Assisted Intelligence

refers to Chatbots commonly used for candidate interviews and other AI technology that can assist human resources practitioners in their work especially in repetitive tasks (Pillai and Sivathanu, (2020). Augmented Intelligence is man and machine integration in decision making with the example of the use of Bots in recruitment and selection through management of candidate experience via 'channels' in scheduling interviews or responding to queries (Pillai & Sivathanu, 2020). Lastly Pillai and Sivathanu (2020) define Autonomous intelligence as a form of AI that does work independently without human intervention, gathering and analysing results for instance, providing candidate selection results from set criterion.

AI has evolved over the years to have inculcable purposes (Martinez, 2019). It has been used in different industrial sectors. Pillai and Sivathanu (2020, p.2600) inform that AI enhanced technology in the form of 'machine learning, virtual reality, bots, robotics, chatbots, robotic process automation, deep learning, internet of things' and augmented reality among others have changed the way human resources function. The intelligence is evolving and it is clear that AI will progressively have the ability to conduct most human tasks and do them better (Martinez, 2019). In simplistic terms, to aid their recruitment and selection practices, South African universities can adopt AI, creating systems that model human behaviour to the extent they can solve multifaceted issues through akin human thought processes (Maheshwari, 2023). AI systems enables integrating bulk data sets with intelligent algorithms to quickly process numerous activities (Maheshwari, 2023). Artificial intelligence provides some degree of insights in data interpretation (Mayo, 2021). A bulky set of data generated by a recruitment ad-response can thus be quickly processed through such intelligent algorithms. According to Maheshwari (2023), for the aforementioned the key tools that power AI in performing tasks almost similar to the human counterpart are machine learning which utilises keyed data using differentiated statistical applications, permitting AI to discern assorted data patterns while deep learning is a superior system of machine learning utilising artificial neural networks in information processing thus discovering extrapolations or outcomes. In a nutshell, using the example of the recruitment ad-response above, a conclusion can be drawn that through inputted algorithms, while machine learning will be useful in drawing a shortlist of candidates, deep

learning will go further through perhaps inferring candidate suitability, culture fit and other likely competence considerations.

Recruitment

Kapur (2018) defines recruitment as the process of identifying, screening, shortlisting and hiring of the potential human resources for the purpose of filling up the position within the organisation. While Klepić (2019) concurs that the definition becomes broader as a process of attracting candidates for job vacancies who possess the competencies, abilities and features requisite for 'successful job performance and goal setting'. Accordingly, the main focus of recruitment is the attraction of the right pool of candidates to select the best from (Klepić, 2019).

Selection

This is the process of selecting the right candidate with prerequisite qualifications and experience for the position. It is picking the most suitable person for the vacancy (Klepić, (2019). The selection process as Klepić (2019) puts it, ideally follows predetermined methods and technique for a specific vacancy in hiring the best talent. The methodology demands determining the potential employee's ability to perform competently through use of a specified criterion in deciding on the best potential employee (Klepić, 2019). Some selection methods can include, screening of candidates, structured interviews, assessments including references and job offer negotiation among others (Klepić, 2019).

Traditional Recruitment and Selection

Traditional recruitment denotes paper-based and face to face conducted candidate hiring. It refers to the sourcing of candidates through traditional print media via job advertisements, manual job boards, recruitment agencies as well as other forms of marketing to draw candidates to apply. The source or channel through which the attraction of the candidates is done can determine the quality and quantity of applications (Shenoy & Aithal, 2018). Shenoy and Aithal (2018) advices that whichever talent attraction methodology used, pertinacity in sourcing tactics are required to 'yield results'. In some organisations, over time, recruitment has evolved to e-recruitment which is familiarly referred to as AI recruitment (Van Esch, Black & Ferolie, 2019).

Vanderbist (2020, p.3) cites Dijkkamp (2019) who proposes four funnel stages of traditional recruitment and selection as; ‘attraction and sourcing candidates through adverts, employer branding and social media’; candidate screening, assessing and engaging are repetitive tasks traditionally done by the human resources practitioners with the goal of creating relations with prospective employees; ‘selecting and hiring’ entails interviews and background checks among others and lastly the ‘analytics, insights and optimise stage which is the overall final candidate selection decision.

Figure 2.2: Four Stages of Talent Acquisition

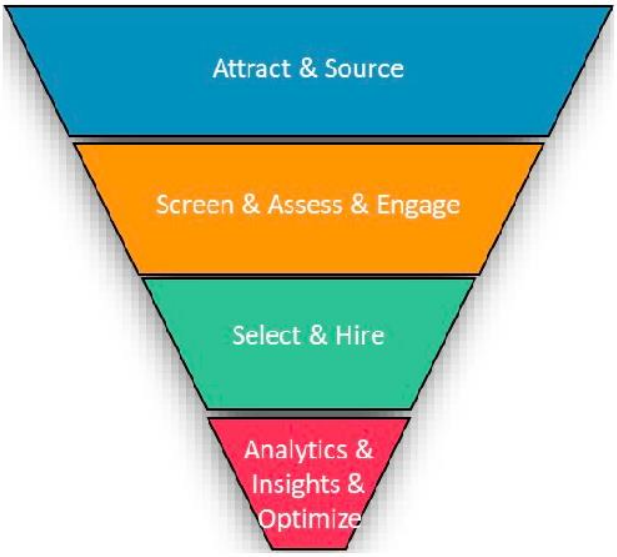

Figure 2.2 Four Stages of Talent Acquisition: Source Vanderbist (2020, p.3) (Adapted from Dijkkamp, 2019)
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Technology according to Vanderbist (2020) has been instrumental in changing the funnel depending on the adoption of the technology from elementary to sophisticated. There are several technology ‘touch points’ in the recruitment and selection cycle that can replace the human element at different levels from Assisted Intelligence, Augmented Intelligence and Autonomous Intelligence (Vanderbist, 2020).

2.2. Hypothesis Development

Adoption of AI exposes an organisations to ‘a plethora of opportunities’, in the public sector (Neumann, Guirguis, Steiner, 2022). South Africa is facing unprecedented levels of unemployment, currently at 35,3% as per the fourth quarter of 2021 (Stats SA, 2022). There is however a skills shortage. Sebola (2015) borrows from Isset Seta (2011) and South Africa (2014) defining scarce skills as occupations with scarcity of qualified and experienced people, currently or anticipated in future due to either the unavailability of such people or prospective candidates existing but not matching the recruitment specifications.

What was true in 2007 as indicated by Mulenga and van Lill (2007) citing then Centre for Development and Enterprise (2007), is that, the characteristics of the labour market in South Africa portray an ever decreasing pool of first-rate talent, emigration of highly qualified talent and diminishing skills development. Mgwebi (2019) believes the challenges encountered by universities in the attraction and retention of academics, particularly black staff, has been experienced by the higher education sector since the dawn of democracy in 1994. Mgwebi (2019, p.3) adds that while ‘seasoned white academics continue to retire’, going to rest with treasured scholarly ‘capital at a loss to academe’, there are not enough black academics filling the void. The matter for this research is not so much about representation, it is about universities enabling their talent strategies through embracing technology by understanding factors that influence such technology adoption. Department of Home Affairs (2022) published a new critical skills list giving universities parameters to recruit expatriate lecturers. This entails entering into an international labour market pool that evidently requires novel recruitment and selection processes as well as paying premium packages for their attraction.

Universities need to have a paradigm shift in their recruitment and selection process by adopting artificial intelligence. Organisations have become woke to the need for requisite, functional and tailored talent sourcing technologies (Allal-Chérif & Sanchez, 2021). There is an increased trend in organisations now adopting AI applications in employee job suitability assessment, screening and selection (Rodney, Valaskova & Durana, 2019).

To comprehend some of the issues with traditional recruitment and selection processes Mkhize (2018) encapsulated it more vividly. Mkhize (2018, p.19) assessed talent acquisition processes of academic staff at 'University of KwaZulu-Natal' observing the regular hiring practices in through use of print media advertisements, internal channels, recruitment agents, employee networks and electronic media radio advertisement among others. Further, Mkhize (2018) identified challenges including lower expertise of academic personnel, amplified talent sourcing outlays and poor conditions of employment for academics.

For solutions to fix the problem, the study places great emphasis on management to ensure the competence of the hired personnel through extensive administrative measures to aid the recruitment strategy. When considering issues of 'social injustice', the proposal is to implement a prescribed talent acquisition model that highlights unwanted prejudice. (Mkhize, 2018). The paper is somewhat devoid of how technologies like AI could be the panacea of the shortcomings of the traditional recruitment practices as described. It is perhaps not surprising because within Universities or Higher Education, research on AI adoption in general is scant and has been mostly confined within such adoption in core university functions of teaching, research and learning or student recruitment for thoroughfare as evinced by the work of (Chatterjee & Bhattacharjee, 2020; Kuleto, Illic & Mihoreanu, 2021).

2.2.1. Perceptions on Artificial Intelligence

An important consideration in literature has been the notion of the AI replacing the human being or human element. It is common cause that the less desirable of recruitment and selection jobs are the mundane, monotonous and admin intensive tasks. Human and machine automation and possibilities of job losses have been researched thoroughly. The World Economic Forum (2020) highlighted the emergence and decline of jobs and skills in the new world of work. Le Roux (2018) assesses the interplay between advancing technology and labour demand. Moyo (2019) remarked Microsoft as concluding that owing to the combination of high unemployment rate in South Africa and the low

appreciation of artificial intelligence, any notion of automation enthusiasm, is smothered by contemplations of unwelcome job loss due to such automation. How does the apprehension by practitioners of the losing their jobs to technologies like artificial intelligence influence their willingness to adopt the system? Through use of Technology Organisation Environment framework, this study generated insights from Human resources practitioners regarding adoption of AI. Such type of study is not available in the South African context.

Various studies in literature consider the human resources function especially as a critical determinant of AI adoption. The perceptions of the Human resources manager especially the use of AI to aid recruitment decision making, are critical (Bhatt, 2022). Albert (2019) considers the views of Recruitment and Selection Practitioners, HR Managers and Consultants. Lisa, Rotan and Simo (2021) investigates the attitudes of recruiters and recruitees in the use of AI within the Sweden context. Through a qualitative research, the researchers observed the challenges in traditional recruitment space using thematic analysis of various stages of recruitment and selection through the lens of the practitioners, enabling inferences that aided literature and provided a basis for their strategic recommendations (Lisa, *et al*, (2021).

Pillai and Sivathanu (2020) used the Technology Organisation Environment (TOE) and Task-Technology-Fit (TTF) quantitatively sampling 562 human resources managers in understanding factors affecting AI adoption in talent acquisition. Pillai and Sivathanu (2020) conclude security and privacy issues have a detrimental effect on adoption while an artificial intelligent technology cost effectiveness, relative advantage, preparedness of human capital practitioners, executive management support, sector adoption competitiveness and backing from AI technology suppliers have an emboldening effect.

Adoption of artificial intelligence research has also been centred on ethical considerations and this represents a major challenge. Kodiyan (2019) investigates ethical issues through a case study of Amazon’s artificial intelligence based hiring tool. Scholars grapple with the question, to what extend do AI enabled tools for instance in recruitment interviews

meet ethical considerations. As in the case of Amazon, Kodiyan (2019) showed that biased data in an artificial intelligence algorithm invalidly led to a preference of male candidates at the disadvantage of females. The exercise exhibited an algorithm weakness. Algorithms are infact inputted by a human element implying their interpretation and the consequences thereof as entirely subordinate on such data. The connotation is therefore, a possibly subjective judgement can be construed as an objective outcome. Ochmann and Laumer (2020) as a result believe the impartiality of AI judgements is solely 'premised upon the Algorithm data'. Literature has weighed the fairness of artificial intelligence, accepting the notion that the construct 'fairness' is a challenge to define in the context of artificial intelligence. Nevertheless, Ochmann and Laumer (2020) suppose within traditional recruitment, humans make more biased decisions. The perceptions of the human resources personnel in considering fairness as a determinant of adoption is worth investigating.

2.2.2. Factors Affecting Adoption of Artificial Intelligence

Global literature on artificial intelligence technological adoption in talent acquisition is gaining momentum in diverse contexts. Several studies explore the efficacy of AI technologies in employee hiring in IT/ITeS Organisations context (Pillai and Sivathanu, 2020); labour-intensive Indian economy (Mukherjee, 2022); emerging economies in the global south (Kshetri, 2020); adoption of artificial intelligence in public organisations (Neumann et al., 2022) whose body of research is said to be growing. There has not been much studies of artificial intelligence adoption within universities especially in aid of staffing.

Chatterjee and Bhattacharjee (2020), explore artificial intelligence within the context of Indian higher education with interest in the mainstream core university activities, attitudes of stakeholders toward artificial intelligence and whether stakeholder behavioural intentions influence adoption. Popenici and Kerr (2017) explored artificial intelligence on higher education teaching and learning. Wang et al., (2021) analyse higher education adoption with a specific interest of gaining teacher perspectives in the Chinese context. Popenici and Kerr (2017) deem AI automation as possessing the potential to operationally

transform university administration. There is definitely a deficiency in literature that requires an empirical study of what may influence this technological spread within recruitment and selection in the context of South African universities.

Europe, Asia and America have the most scholarly research on AI adoption in recruitment and selection. Pillai and Sivathanu (2020) predicted usage of AI enhanced business processes in over 22% of companies in India, while Kshetri (2020) reports in a survey conducted by Venngage that, 61% of companies in the US are using artificial intelligence to improve human resources management. There is scant research within the African context in general and within South Africa in particular. It would be sensible to understand the factors influencing AI uptake within South Africa. An explorative study on adoption influences of AI among South African universities provides a unique context which has not been done before in literature and a worthwhile research gap to cover. South African industries have thus far made significant investment in AI adoption in general and most AI powered tools are being piloted (Moyo, 2019). There is need to interrogate artificial intelligence adoption within such a context to contribute to this budding trend across the world.

Artificial intelligence as a transformation imperative has been demonstrated in a number of studies. Much scholarly work has focused on the remarkable potential of artificial intelligence in refining decision making procedures and warranting efficacy in the recruitment processes (Ore & Sposato, 2021; Singh & Shaurya, 2021). There is an acceptance among scholars on the limitations of traditional recruitment and selection especially the ‘limited abilities’ of humans (Johansson, Harranen and Mccauley, 2019). Much research in AI technology adoption has therefore focused not only on how AI has transformed the recruitment space as in the case of Charlwood and Guenole (2022) and Tejaswi and Neelima (2020) research has relatedly considered the applicability and usefulness of various AI enabled tools, applications and platforms and the reasons thereof. Albert (2019) is convinced most companies adopt chatbots/CRM apps, admin-related task automation and candidate screening AI powered software. It would be interesting to explore which among these applications do Human resources personnel

regard as the most attractive to use. This research however was limited to understanding perceptions that influence adopting artificial intelligence.

Literature has demonstrated that adoption of artificial intelligence in talent acquisition takes various forms depending on perceived advantages. Relative advantages have a positive effect on AI technological adoption, chiefly AI technology's ability to process huge data volumes is noted by (Pillai & Sivathanu, 2020; Upadhyay & Khandelwal, 2018). There are also different stages of adoption which are differences in AI integration by various organisations and in diverse industries (Lisa et al., 2021). Scholars have grappled with understanding the stage of the hiring process where AI adoption is most suitable. Bhatt (2022) resolves the sourcing and screening stages as most critical. The relative advantage is therefore linked to what users may perceive as such within their distinct contexts. This research aimed at exploring the effects of relative advantages through the Technology Organisational Environment (TOE) model to understand the perceptions of such advantages within the context of South African universities to aid likely strategies.

As this literature review would have shown, much of artificial intelligence body of literature has concentrated on the type of technology and techniques that organisations can pursue to enable their processes. There is a gap in understanding AI adoption especially within South African universities. A manager within higher education environment might consult literature and find reasons why artificial intelligence adoption is critical but save for a few articles, struggle to understand how such adoption can be achieved.

2.2.3. Strategies to Increase on Adoption

Bhatt (2022) believes efficient adoption of AI presupposes decisions of strategic importance to the company. It is critical to make informed decisions prior to adoption to ensure such adoption is useful in the organisational context. A central theme from literature is research on readiness for AI adoption. In the empirical search of factors affecting artificial intelligence adoption, scholars wrestle with understanding readiness. Stenberg and Nilsson (2020) cites Armenakis *et al.* (1993) who indicate as a change

management imperative, readiness is a concept characterised by the precursor to either support or resist change. Stenberg and Nilsson (2020) uses TOE to anticipate readiness of government departments use of AI technology. Readiness might also beg the question of organisational implications (Ore & Sposato, 2021). Understanding the current organisational technology, measuring top management support, gauging complexity, the regulatory environment and staff capacity amongst others, can demonstrate organisational obstacles in adoption that would qualify the right strategies for adoption.

Artificial intelligence adoption studies have demonstrated the competitive advantages brought about by adoption of AI for improved business process. Alsheibani, Cheung and Messom (2018), believe adoption of AI is easier said than done citing Gartner (2017a) who proclaimed 59% of entities are still researching on whether to adopt artificial intelligence while 6% have already deployed the technology. Critically therefore this paper looked at factors affecting the adoption of AI including assessing the influence of perceived relative advantages of doing so and this permitted an analysis of strategies that facilitates such adoption at an organisational level. Literature shares a common thread that for AI to be adopted effortlessly, the design of its applications and systems must be in congruent and amalgamate smoothly with existing company infrastructure and technology (Alsheibani et al., 2018).

2.3. Theoretical Frameworks in Technological Adoption

The impact of technology on organisational processes and outcomes has been a longstanding topic of interest for business researchers. They have explored how various types of technologies, such as information systems, automation, artificial intelligence, and social media, affect the way organisations operate, innovate, compete, and adapt to changing environments. Hoti (2015) cites Geroski et. al., (1993) who states that technological innovation had been subjected to theoretical and empirical studies and is regarded among scholars as a critical determinant of organisational sustainability or competitive advantage. Literature thus shows a continual growth and refinement of the theories in technological innovation and adoption.

Pillai and Sivathanu (2020), explained that Technology Acceptance Model (Davis and Davis, 1989); Diffusion of Innovation (Rogers, 2003) and (Venkatesh, et al., 2009) Unified Theory of Acceptance and Use of Technology, are chiefly 'techno-centric', explicating adoption from an individual perception as compared to a TOE model which considers adoption comprehensively through a rounded organisational perspective and thus providing a more thorough explanatory power. Having assessed the varied merits of the Technology Organisation and Environment model, the researcher utilised TOE framework as it encapsulates all the constructs and subconstructs that enable the conceptualized framework which better explains adoption from an organisation perspective.

2.3.1. Technology Acceptance Model

Koul and Eydgahi (2017) discusses the 'Technology Acceptance Model' (TAM) and conclude the model is extensively used, pertinent and instrumental in technological adoption. Technology Acceptance Model was proposed by Davis (1989). It originated from the psychological theory of reasoned action and theory of planned behaviour (Holden & Karsh, 2010).

Figure 2.3 Technology Acceptance Model

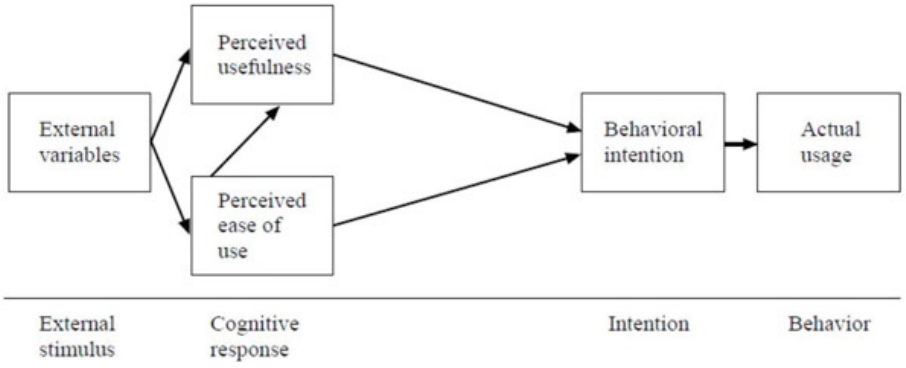

Figure 2.3: Technology Acceptance Model. Adapted from Davis & Venkatesh, 1996, p.20.
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In the adoption of technology, the central constructs of Technology Acceptance Model according to Davis (1989) are considerations of the technology's; 'Perceived usefulness', defined as the extent to which the individual user believes use of the specific system

‘would enhance’ on the job performance. Similarly, according to Davis (1989) ‘Perceived ease of use’, is critical, referring to extent to which the user ‘believes that using a particular system would be free of effort’, in other words, effortless, free of physical and mental effort. The ‘behavioural intentions’ of the user is also critical as a major determinant if the user will eventually use the system (Chuttur, 2009). Artificial intelligence technological adoption involves job augmentation through integration of human and machine. The model does not address the apprehension a human resource practitioner might feel as ‘automation’ has been associated with inevitable job loss. The primary constructs of perceived usefulness and ease of use are as it seem not the only determinants of artificial intelligence acceptability in this example.

In research Technology Acceptance Model has been used for information systems adoption by organisations and has also been used in literature in other contexts like health care (Holden & Karsh, 2010). Chuttur (2009) acknowledges how it has been refined, evolved modified overtime becoming ‘a leading model in explaining and predicting system use’. Critics to the model also believe ‘Technology Acceptance Model may have attracted more easy and quick research’ but the pertinent issue of technological acceptance, (Chuttur, 2009). Ajibade (2018) questions its applicability in an organisation setting believing the model has not been designed for the institutional or business context application but for personal use of technology.

2.3.2. Technology Acceptance Model 2

Technology and Acceptance Model 2 (TAM2) put forward by Hoong et al., (2017) as well as Venkatesh and Davis (2000) is a revamp of Technology Acceptance Model incorporating social influencing processes and cognitive instrumental processes as additional theoretical constructs (Venkatesh & Davis, 2000). Hoong, Thi and Lin (2017), explain that, subjective norm is hypothesized to have a direct effect on the intention of an individual to choose to perform a certain behaviour and found to have direct effect on intention over Perceived ease of use and Perceived usefulness.

Figure 2.4 Technology Acceptance Model 2

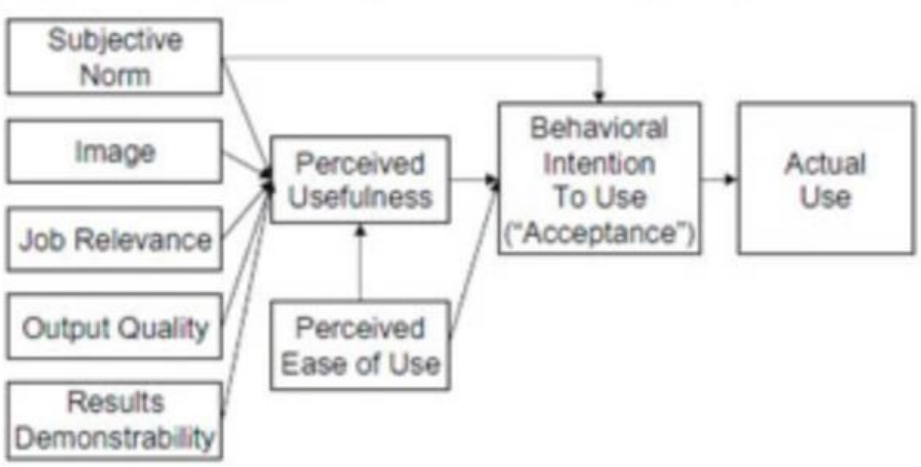

Figure 2.4: Technology Acceptance Model 2. Adapted from Holden & Karsh, 2010, p.161.
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Technology Acceptance Model 2 postulates that one relies on the 'fit between their job and the performance outcomes of using the system which in turn determine the persons perceived usefulness of the system based on the job relevancy'.

2.3.3. Technological Organisation and Environment Framework (TOE)

Technology Organisation and Environment framework (TOE) provides a good diagnosis for AI adoption (Fleischer & Chakrabarti, 1990). Jere and Ngidi (2020) inform that the TOE model is a classical framework used to predict an organisation's intention to adopt technological innovation through expounding on the three constructs namely the technological, organisational and the environmental contexts. With artificial intelligence adoption still in its infancy in South Africa, it is critical to have a comprehensive understand of factors that may influence such adoption through use of the TOE framework.

Figure 2.5: Technology, Organisation and Environment Model

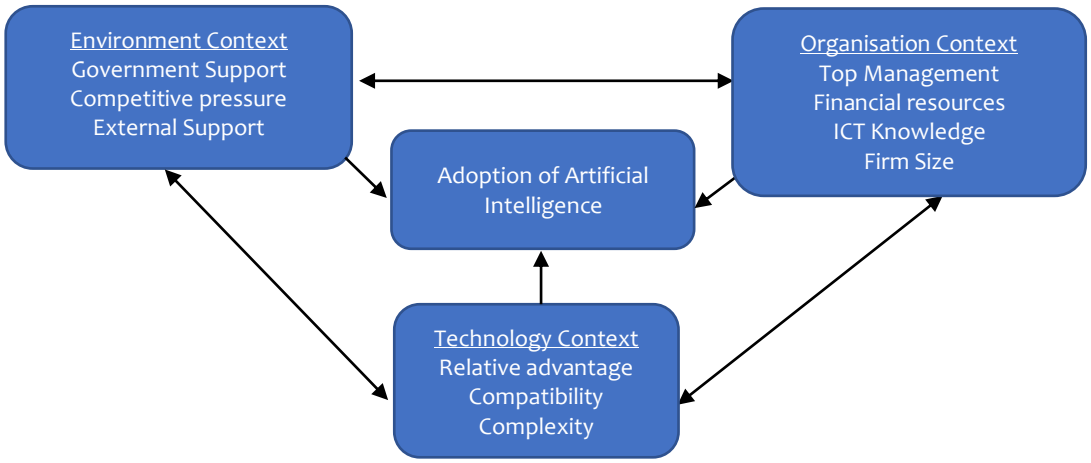

Figure 2.5: Technology, Organisation and Environment Model. Source Jere and Ngidi, (2020)

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Technology Context

According to Oliveira and Martins (2011) technological context represents both the internal and external technologies appropriate to the entity including the technological infrastructure and personnel technical skills. Hoti (2015) as well as Jere and Ngidi (2020) placed emphasis on the internal and external factors impacting productivity and thus an inclination towards advancement of adoption. Current technological expertise and infrastructure in a university has an influence on AI adoption as a novel innovation. Metaxiotis (2009) asserts that having the technological infrastructure is not an end in itself but rather, it calls for innovative and competent employees that enable sustainable competitive advantages.

Organisation Context

Judges the ability of a university to adopt artificial intelligence from organisational determinants of size, management structure, decision making and organisational conduits. These are mostly internal factors that have an impact on the adoption process. The degree to which top executives within universities are involved in transformative change is imperative, it can permit or impede technological adoption. The size and scope of the university are also critical determinants of its ability for a paradigm shift.

Environmental Context

This refers to environment or particular industry in which the university conducts business. This would imply governance, through the Department of Higher Education and Training, Council on Higher Education (CHE), South African Qualification Authority (SAQA) and competitive interactions with other universities and business partners in the environment as determinant factors in the adoption of artificial intelligence. Does the current Higher Education environment support the adoption of this innovation by universities?

Using TOE Model

The research purpose of establishing factors influencing adoption of artificial intelligence technologies in recruitment and selection processes among South African universities were expounded on using the framework. The technology, organisation and environment constructs and their sub-constructs can be evaluated on a Likert scale to help understand such influences on artificial intelligence adoption. In justifying using the model, Pillai & Sivathanu (2020) highlight TOE as a dominant framework at an institutional level of technological adoption with a better explanatory power of internal and external organisational factors that influences adoption.

Yousra and Khalid (2021) notes that in addition to the constructs as contextualized by the Technology Organisation Environment model, there are other behavioural variables that could be considered as factors that can have an impact on adoption. The sub-constructs of; subjective norms, awareness, trust, resistance to change and perceived substitution crisis can help in appreciating the benefits and risks on an individual and on an organisational scale.

2.4. Conceptual Framework

The conceptual framework has been adapted from Pillai and Sivathanu (2020). The framework is based on the literature review and Technological Organisation and Environment (TOE) theoretical framework constructs to examine the research questions. According to Pillai and Sivathanu (2020) citing Awa et al., (2015; 2017b), the framework allows for inclusive perceptiveness and a broader knowledge in expounding while

enabling visualising of technological adoption from an organisational outlook. The model thus considers essential constructs relevant to technological adoption within the human resources and recruitment arena.

Figure 2.6: Conceptual Framework

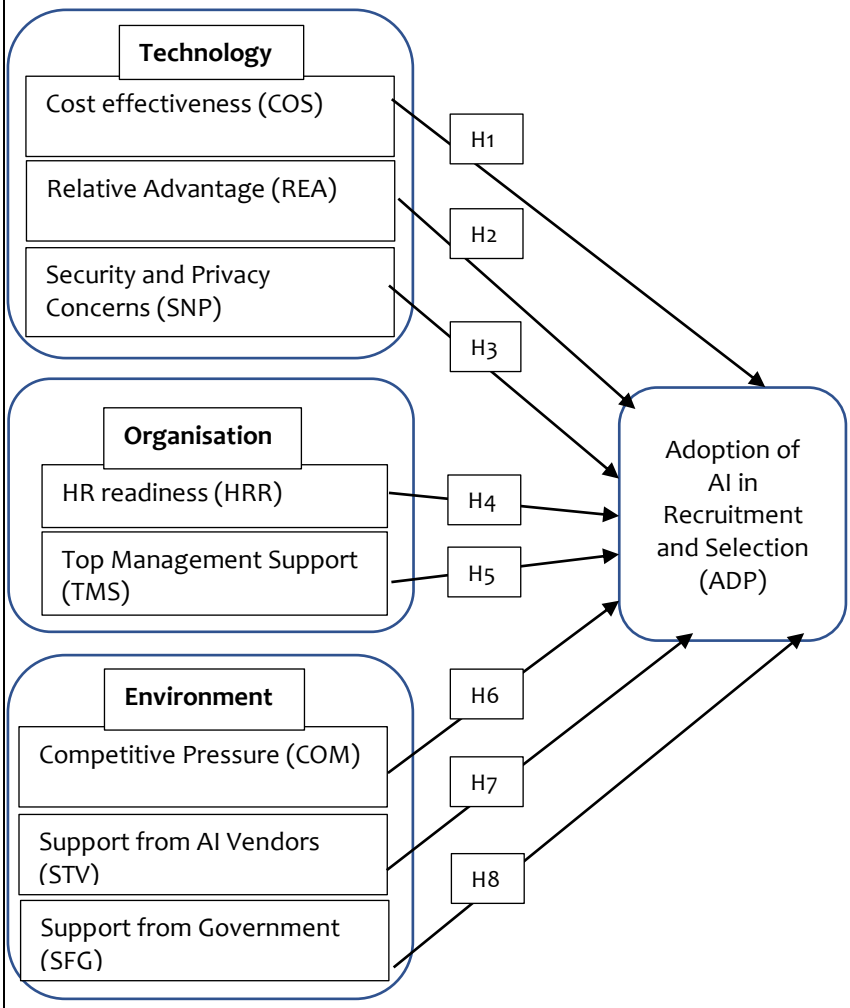

Figure 2.5: Conceptual Framework Source: Pillai & Sivathanu, (2020) Adapted from (Depietro et al., 1990: Goodhue and Thomson 1995a).

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2.4.1. Technological Factor Sub-constructs

Cost Effectiveness (COS):

The financial health of universities is an essential subconstruct of the organisation context. Having the financial muscle to adopt artificial intelligence is a critical determinant

of the ability to adopt the innovation. Cost must therefore the incurred for the adoption of artificial intelligence. Premkumar and Roberts (1999) indicated that cost is calculated and evaluated as ‘cost-effectiveness’, which means the benefits generated out of artificial intelligence should outweigh the cost of adoption. In recruitment, artificial intelligence has been shown to ensure accuracy and quick recruitment and selection turn-around time, reducing mundane and monotonous tasks, allowing HR personnel to focus their efforts elsewhere, saving money and time.

H1. Cost Effectiveness (COS) of Artificial intelligence (AI) for Recruitment and Selection (RS) will positively affect the adoption (ADP) of artificial intelligence for Recruitment and Selection (RS).

Relative Advantage (REA):

The relative advantage of adopting artificial intelligence in the recruitment and selection processes are innumerable, inclusive of passive talent sourcing, reduced candidate screening bias, predictive analysis and chatbots enabling candidate engagements. As Jere and Ngidi (2020) in our instance related, measures of convenience, satisfaction and high standards would be critical determinants of adoption. Relative advantage is the magnitude to which a novel technology is deemed an improved enhancement in comparison to the prior technology it replaced (Pillai & Sivathanu, 2020). For artificial intelligence to be adopted, its relative advantage should be viewed to be better than the traditional recruitment process. Such advantages as brought about by artificial intelligence to include better talent acquisition, screening and diversity management.

H2. Relative advantage (REA) of Artificial Intelligence (AI) for Recruitment and Selection (RS) will positively affect Adoption (ADP) of Artificial Intelligence (AI) for Recruitment and Selection (RS).

Security and Privacy Concerns (SNP):

Pillai and Sivathanu (2020) quote Zhu *et al*., (2006) by defining SNP as the magnitude where information system and technology are deemed unsafe or risky in business

undertakings and data sharing. Security being one of the determinants of adoption of artificial intelligence in an entity (Zafar, 2013). For handling private and sensitive candidate data and information, security is critical (McGovern et *al.,* 2018). Ethical considerations have been noted to be an issue when considering interviewing through artificial intelligence systems. The hypothesis considered the possible cause and effect relationship.

H3. Security and Privacy Concerns (SNP) in Artificial Intelligence negatively influence the Adoption (ADP) of Artificial Intelligence (AI) for Recruitment and Selection (RS).

2.4.2. Organisational Sub-constructs

Human Resources Readiness (HRR):

The Human resources component is a critical determinant of AI adoption. Pillai and Sivathanu (2020) considers HRR construct not on an individual basis but the Human resources department's skills, resources and financial budget to adopt AI for recruitment and selection. The human resources departments could still be trying out new technologies but may still be using traditional recruitment and selection methods (Albert, 2019).

H4. Human Resources Readiness (HRR) positively influences the Adoption (ADP) of Artificial Intelligence (AI) for Recruitment and Selection (RS).

Top Management Support (TMS):

As has been demonstrated by Moyo (2019), due to high levels of unemployment in South Africa, any form of advanced automation is usually met by apprehension of the likelihood of job loss. It is suggested therefore that executive management provide leadership in the change process. Top management can be a barrier towards adoption (Yousra and Khalid, 2021). Change must be a top-down approach, the executive themselves should understand and appreciate the need for AI and its benefits.

H5. Top Management Support (TMS) positively influences the Adoption (ADP) of Artificial Intelligence (AI) for Recruitment and Selection (RS).

2.4.3. Environment Sub-constructs

Competitive Pressure (COM):

Hungund and Mani (2019) postulates that decisions of an organisation are contingent on its environment. The extent to which there is competitiveness among South African universities in the adoption of artificial intelligence is very important but may not be a critical determinant of adoption especially in aid of recruitment and selection processes. Priority competitiveness could be vested in core deliverables like student throughput, research, teaching and learning. So, pressure to adopt might be caused by environmental considerations.

H6. Competitive Pressure (COM) positively influences the Adoption (ADP) of Artificial Intelligence (AI) for Recruitment and Selection (RS).

Support from Technology Vendors (STV):

According to Pillai and Sivathanu (2020), any new technology application especially with the expertise required for implementing artificial intelligence, requires support from technology vendors to service the technology while in use. Infact, vendor application development, implementation and usage have an impact on adoption. The need for customization and continued support will be critical for recruitment and selection artificial intelligence-based technology (Pillai and Sivathanu, 2020).

H7. Support from Technology Vendors (STV) positively influences the Adoption (ADP) of Artificial Intelligence (AI) for Recruitment and Selection (RS).

Support from Government:

The South African government has been on the forefront in pursuing information technology advancement and innovation. The support from the Department of Higher Education and Training is likely to have an influence on the adoption of artificial

intelligence in recruitment and selection. Department of Higher Education and Training (2019) observed the need to improve black academics within universities. Such a talent acquisition exercise might be improved by an aligned adoption of artificial intelligence.

H8. Support from Government (SFG) positively influences the Adoption (ADP) Artificial Intelligence (AI) for Recruitment and Selection (RS).

2.5. Conclusion

The chapter was able to elucidate on the research problem to expose the knowledge gap through an in-depth literature review subsequently leading to a conceptual framework of the study. Literature has emphatically shown although there is an upward trend in that research on AI adoption in recruitment and selection, within the South African context especially, such research in universities is non-existent save for technology adoption literature in the core university functions of teaching and learning. Literature has also demonstrated the advantages of adopting artificial intelligence in recruitment as opposed to the disadvantages of sticking to traditional recruitment and selection processes.

The perceptions of AI adoption and other constructs from a Technology Organisation and Environment (TOE) framework have a probable influence on adoption. The TOE framework formed the basis of the study.

CHAPTER 3: RESEARCH APPROACH, DESIGN & METHODOLOGY

In the preceding chapter a comprehensive review of literature was conducted, and theoretical frameworks were used to elucidate the research questions. The research questions are as indicated in Section 1.2.4. Chapter 3, Section 3.1 discusses the research approach whereas Section 3.2 is the research design. Section 3.3 is about the target population, sampling and data collection. Section 3.4 deals with data processing and analysis. Section 3.5 tackles validity and reliability while Section 3.6 concludes with research ethical consideration.

3.1. Research Approach

The research methodology requires that a suitable research strategy, design and techniques are selected in accordance with strict requirements of the study. Selected techniques are aligned to the research problem focusing on AI adoption in the talent acquisition practices among South African universities.

A research approach is defined by the Us.sagepub.com (2015), as ‘the procedures for research that span the steps from broad assumptions to detailed methods of data collection, analysis and interpretation.’ It is the breaking of the problem into component sub-problems and using data in their evaluation (Neumann *et al.,* 2022). The research approach or strategy can take the form of a quantitative, qualitative and mixed methods.

Qualitative research approach is concerned with exploration and understanding the meaning acknowledged to a human or social issue by groups or an individual (Us.sagepub.com, 2015). Qualitative data is typically collected at the participants setting while data analysis is an inductive analysis of general themes and interpretations of meaning of the data. Quantitative research is useful in testing ‘objective theories by examining the relationship among variables’, which are measurable on instruments and data analysis done using statistical procedures (Us.sagepub.com, 2015).

The research questions, literature review and conceptual framework are thus developed for interpreting research findings together with strategies used in a similar research (Pillai

and Sivathanu, 2020). This study made use of the quantitative research design. Leavy (2017) notes that quantitative research is characterised by deductive approaches critical in this paper to prove, disprove or lend credence to the Technology Organisation and Environment theory. The quantitative approach according to Leavy (2017) allows for the testing of variables, real patterns, correlations and causal relationships.

In exploring adoption of AI for talent acquisition, Pillai and Sivathanu (2020) similarly used a quantitative research strategy. The advantages of using a quantitative approach would be its allowance for a broader study that involves a bigger sample which allows for greater generalisability. Leavy (2017) rightfully concludes that quantitative approach is appropriate when, as in this research the 'primary purpose is to explain and evaluate' relationships. The need for validity and reliability ensures that researcher bias can also be eliminated (Queirós, Faria & Almeida, 2017). In building and testing hypothesis there is use of clear objectives and guidelines devoid of the researchers' bias.

3.2. Research Design

Akhtar (2016) notes research design as the structure of the research, the glue that binds the essential elements in a research together. The design is the plot, structure and strategy and investigation concaved so as to obtain, ensured to search question and control variance (Akhtar, 2016). Research design affords the basis, structure and framework for data collection and interpretation. Bryman (2012) provides the types of research designs to be inclusive of experimental design, cross-sectional or survey design, longitudinal design, case study design and comparative design.

In this study, there was need to investigate cause and effect relationships between variables. The research therefore makes use of cross-sectional research design or survey design which utilises quantitative data collection from many individuals at a single point in time (Thomas, 2003).

Cross-sectional design will allow for quick data collection from different places, in this case universities. It allows for research investigation of relationships between variables

without manipulating or controlling them (Bhandari, 2022). The cross-section design is also relatively inexpensive yet quick to conduct.

3.3. Target Population, Sampling & Data Collection

3.3.1. Target population & Participant Recruitment

In defining 'target population', Rahman, Tabash, Salamzadeeeh, Abduli and Rahman (2022) affirm it as a collection of individuals or objects 'about which the researcher aims to deduce a broader generalisation' on. In this study, the target population were Human Resources practitioners within the 27 universities in South Africa. The respondents being individual adults aged above 18 years, involved in the recruitment and selection function.

3.3.2 Sampling

Vehovar, Teopoel and Steinmetz (2016) define a sample as 'subset of a population'. A researcher, as Vehovar *et al.,* (2016) puts it, 'surveys the units from the sample' in order to make generalization about the population. There are two types of sampling, which are probability and non-probability sampling (Elfil & Negida, 2017; Shorten & Moorley, 2014). This study focused on non-probability sampling where the participants were selected using some discretion. Out of the study population, purposive sampling was conducted. The sampling method was conducted through focusing on the human resources staff within the universities. The sampling method assisted the researcher in directing the resources towards the potential participants. Out of the population of HR practitioners from 27 universities in South Africa, the sample size was purposively set at the researcher's convenience as well as the HR practitioners involved in recruitment and selection within the universities. The sample size determined was then 125 personnel directly involved in recruitment and selection within these universities.

3.3.3. Data Collection

Data collection is critical in research. The collected data was analysed to draw inferences in answering the research questions. Johnson and Christensen (2014) notes that

collection of the data in research is normally done through surveys, completion of questionnaires or through interviews. Data was collected through use of an online self-administered questionnaire created using Qualtrics. The recruitment of respondents was tailored according to the POPI Act compliance requirement of different institutions. Most institutions allowed the questionnaire link to be shared with prospective respondents via an introductory email. A few preferred the introductory email together with the questionnaire to be distributed to the human resources practitioner either the head of department or an elected contact through emails or advertisement on the university's electronic board.

3.4. Data Processing and Analysis

Processing of data takes the form of converting data into machine-readable form. This means data cleaning, coding and cataloguing to enable analysis of the same. Neuman (2015) notes that coding is the reorganization of data using a statistical system while assigning value to it.

For this research, data was collected using a self-administered questionnaire link formed using Qualtrics. The link having been shared with participating universities through the agreed channel, mostly via email and electronic notice board. The data cleaning instruments were Ms Excel and SPSS. In SPSS numerical codes for responses were assigned to the data especially for incorrectly captured data or data with missing values. Use of SPSS enabled detection and removal of outliers and use of descriptive statistics allowed for the correction of range values.

Statistical hypothesis testing was conducted through correlation and as well as structural equation modelling (SEM) in testing relationships among the variables using Smart-PLS 4 software. Structural Equation Modelling (SEM) is a statistical technique used to analyse complex relationships among observed and latent variables. It integrates both measurement models (to assess the validity and reliability of the measurement instruments) and structural models (to examine the relationships among variables). SEM involves three key components: latent variables, observed variables, and paths. Latent

variables are constructs that are not directly measured but inferred from observed variables. Observed variables are the variables that are directly measured. Paths represent the hypothesised relationships between variables.

Validity and reliability are crucial aspects of measurement in SEM. They ensure that the measurement instruments used in the model accurately capture the constructs of interest and provide consistent results. Some of the different measures of validity and reliability commonly used in SEM are:

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Validity and reliability are crucial aspects of measurement in SEM. They ensure that the measurement instruments used in the model accurately capture the constructs of interest and provide consistent results. Here are different measures of validity and reliability commonly used in SEM:

a. Construct Validity. This refers to the extent to which the measurement instrument accurately captures the intended construct. Several measures are commonly used to assess construct validity, which are:

    - Convergent Validity. It examines the extent to which different indicators of the same construct are highly correlated. This can be evaluated using measures like factor loadings, average variance extracted (AVE), and composite reliability (CR).

    - Discriminant Validity. It assesses the distinctiveness of different constructs by examining whether the indicators of one construct are more strongly related to

each other than to indicators of other constructs. This can be evaluated through measures such as the Fornell-Larcker criterion, cross-loadings, and heterotrait-monotrait ratio (HTMT).

b. Reliability. Reliability measures the consistency and stability of the measurement instrument. Two common measures of reliability in SEM are:

   - Internal Consistency. It assesses the interrelatedness or consistency among the indicators of a construct. Common measures include Cronbach's alpha and McDonald's omega.

   - Test-Retest Reliability. It examines the stability of the measurement instrument over time by comparing measurements taken at two different time points.

c. Measurement Error. SEM takes into account measurement error by modelling the relationship between latent variables and observed indicators. The measurement error can be estimated using various techniques such as the residual variance or error variance.

3.5. Variables

The study engaged a number of variables that were used to measure the adoption of AI in the recruitment and selection. Eight different variables were employed to serve this purpose. These were grouped in three. The three groups were technology variables, organisational variables and environmental variables. Under technology variables, the three variables were cost effectiveness, relative advantage as well as security and privacy concerns. Human resources readiness as well as Top Management Support were under organisational variables. Subsequently, under environmental variables were competitive pressure, support from technology vendors as well as support from government. The choice of variables as well as constructs was inspired by theory, as in studies as such Pillai and Sivathanu (2020) and Yoon and George (2013). The inclusion of these variables in the study was sustained by the Cronbach’s alpha reliability measures of at least 0.7. The Cronbach alpha scores are presented in Table 4.2 in the chapter that follows.

3.6. Validity and Reliability

Reliability is a measure of the consistency and stability of a measurement instrument. It assesses the extent to which the instrument produces consistent results across different conditions, times, or items. There are several commonly used methods to measure reliability, such as split-half reliability, Cronbach alpha, test-retest reliability and inter-rater reliability. This study tested internal consistency reliability through the use of the Cronbach Alpha. The Cronbach's Alpha assesses the extent to which items within a scale or construct are interrelated or consistently measure the same underlying concept. Cronbach's alpha values range from 0 to 1, with higher values indicating greater internal consistency. A value of 0.70 or higher is generally considered acceptable.

On the other hand is validity. Validity is measured using various methods to assess the extent to which a measurement instrument accurately measures the intended construct. Several measures can be used to test for validity such as expert judgement, content validity index, concurrent validity, predictive validity, factor analysis as well as convergent and discriminant validity testing. This study utilised the factor analysis as well as the convergent and discriminant validity testing. Factor analysis identifies the underlying factor structure of the measurement instrument. By analysing the intercorrelations among items, factor analysis helps confirm that the items are indeed measuring the intended construct. Convergent and discriminant validity testing evaluate the degree of convergence and distinctiveness among different indicators or constructs.

3.7. Ethical Considerations

It was essential to ensure ethical considerations were reflected on so as to ensure quality standards of the research and circumvent unethical conduct within the study. Ethics is concerned with the honest, principled and moral values constituting the rules of conducting research. This researcher ensured ethical considerations were ‘implied’ and observed in every step of the research process.

Connelly (2014) mentioned the importance of informed consent of the participants, in this case where the Human Resources practitioners were completing the surveys. Such

consent had to be given voluntarily and participants had to understand what was required of them and competent to give such consent without being coerced, (Connelly, 2014). The intention of ethical consideration is to generate trust and ensure participants feel respected. The confidentiality and anonymity of respondents was guaranteed through the process and thereafter. No biographical data or name of institution were collected.

The researcher ensured strict adherence to all ethical considerations as guided by the issued ethical clearance certificate and gate keepers' permission of other universities. The participating Human Resources practitioners were given informed consent forms and all necessary information prior to the commencement of the survey. Data is stored in a password encrypted database and collection of such data was solely for academic purpose. Transparency and honesty is paramount. It involved open communication and the ability of the respondent to withdraw participation at any point in the process. Appendix 1.1 of the informed consent form shared with respondents has been included as part of this submission.

Further, the researcher applied and obtained the ethics clearance from the Wits Business School before embarking on any data collection. The ethics clearance form is under appendix 2.1. Moreover, the researcher applied for gatekeepers permission from all the universities where the study data was obtained, evidence of such is under appendices 2.2 to 2.9.

3.8. Conclusion

This chapter highlighted the research approach, design, procedure and methods to be used. The study used a quantitative research strategy as well as a survey design used to collect data for analysis from participants. In terms of sampling, the research made use of probability sampling for data collection via a self-administered questionnaire.
Data analysis was conducted through use of SPSS and Smart-PLS 4 software. The systems was used to code, clean analyse data. Reliability and validity measures were considered while strict compliance with ethical considerations was strictly observed.

CHAPTER 4: ANALYSIS & PRESENTATION OF RESEARCH RESULTS

4.1. Introduction

In the preceding chapter, the research strategy, design, procedure and methods, data and information collection processing and analysis, as well as the strengths and weaknesses of the research were comprehensively presented. This chapter, on the other hand, focuses on presenting the research results, which were visually represented by means of bar graphs and statistical tables. In order to establish the credibility of the research, Section 4.2 presents the results of the reliability and validity tests. Furthermore, Sections 4.3, 4.4 and 4.5 sheds light on the research questions and briefly on various strategies that can be employed to improve AI adoption in recruitment and selection processes.

4.2. Reliability Tests

In order to ensure the quality and accuracy of the data collected, the researcher tested the data collection instrument for internal consistency and construct reliability. To test for reliability, the researcher employed the use of Cronbach's alpha (α). The questionnaire used in the study consisted of a total of 26 items that were closely related to the research questions being investigated. To collect responses from the participants, the researcher utilized a 5-point Likert scale that ranged from 1 to 5. The values assigned to each point on the scale were as follows: 1 indicated "Strongly disagree", 2 indicated "Somewhat disagree", 3 indicated "Neither agree nor disagree", 4 indicated "Somewhat agree", and 5 indicated "Strongly agree".

After conducting reliability tests for the entire survey simultaneously, further tests were carried out to determine the reliability of each of the survey questions that measured the same construct. A Cronbach's alpha (α) coefficient greater than 0.7 was deemed acceptable according to the rule of thumb. The researcher tested the internal consistency of the items related to the research questions in order to ascertain the consistency of the indicators that make up the scale or index, and to ensure that the scores were related to one another (Bryman, 2016).

Table 4.1 presents the overall Cronbach's alpha (α) coefficient, which was found to be 0.879. This value is considered to be an acceptable level of internal consistency, as it exceeded the minimum threshold of 0.7. By testing for internal consistency and construct reliability, the researcher was able to ensure that the data collected was reliable and accurate, which ultimately enhances the credibility of the research findings.

Table 4.1: Reliability tests for all constructs

Reliability Statistics

Cronbach's Alpha	N of Items
.879	26

Further, after running the reliability for all the constructs simultaneously, the researcher further tested for reliability of related constructs. Table 4.2 illustrate the results.

Table 4.2: Reliability tests for questions measuring the same construct.

Construct	Cronbach's alpha	N of Items
COS (cost effectiveness)	.841	3
REA (relative advantage)	.886	5
SNP (security and privacy concerns)	.795	3
HRR (human resources readiness)	.740	3
TMS (top management support)	.805	3
COM (competitive pressure)	.865	3
STV (support of technology vendors)	.804	3
SFG (support from government)	.891	3
Overall Cronbach Alpha	**.879**	**26**

The tests performed in Table 4 illustrates Cronbach Alphas greater than 0.7, which further shows that all the constructs are reliable. Consequently, none of the constructs was removed from further analysis.

4.3. Descriptive Statistics

To address the research questions related to the adoption of AI in talent acquisition practices of South African universities, descriptive statistics were performed on all survey questions. Descriptive statistics involve the use of measures such as mean, median, mode, range, and standard deviation to describe the data collected. By performing descriptive statistics, the research obtained a clear understanding of the data and identified trends and patterns in existence.

Descriptive statistics were performed on all 26 survey questions, including the questions relating to factors that exert influence on AI adoption in recruitment and selection processes of South African universities, and the strategies for enhancing adoption. The data collected through the 5-point Likert scale was analysed using frequency tables, histograms, and other graphical representations to provide a visual representation of the data.

Descriptive statistics enabled the researcher to determine the mean, median, mode, and range of responses for each survey question. Additionally, it enabled the identification of any outliers and determination of the variability in responses. The results of the descriptive statistics provided a summary of the data collected. The use of descriptive statistics is an important step in analysing data collected through the survey. It provided a comprehensive understanding of the collected data and helped answer the research questions related to artificial intelligence adoption in recruitment and selection processes among South African universities.

4.3.1. Cost effectiveness of AI adoption in relation to traditional methods

The first three questions from the survey apportioned focus on cost effectiveness of artificial intelligence adoption in the recruitment and selection practices among

universities. Table 4.3 illustrates the descriptive statistics for the questions relating to cost effectiveness.

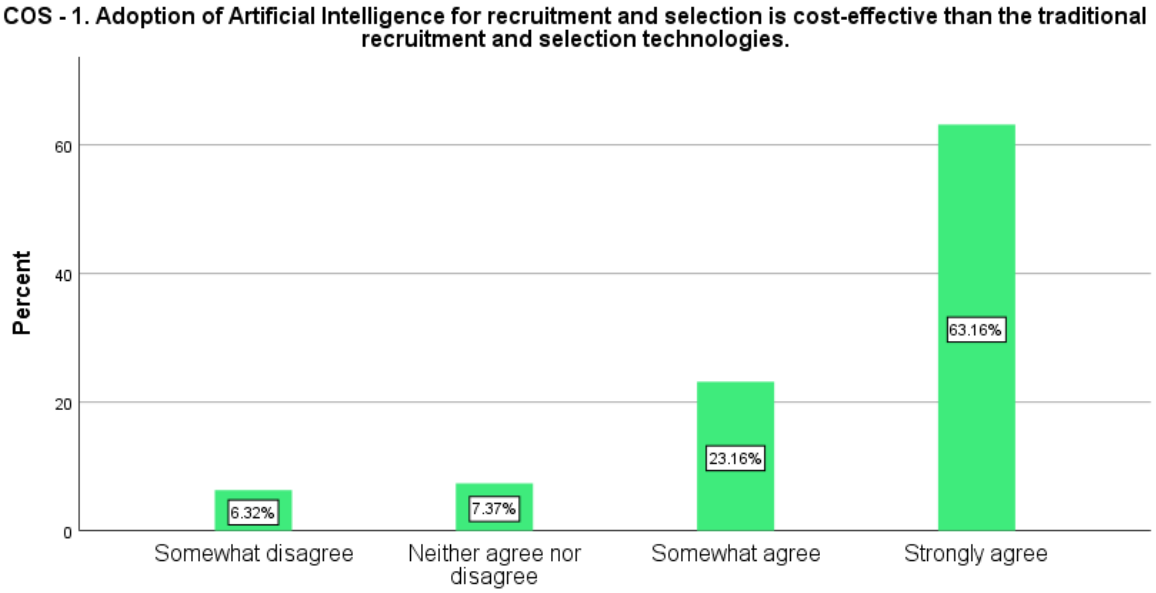
Table 4.3: Cost effectiveness of AI adoption

Statistics

		COS - 1. Adoption of artificial intelligence for recruitment and selection is cost-effective than the traditional recruitment and selection technologies.	COS - 2. Adoption of artificial intelligence for recruitment and selection saves the cost of other technology and manpower required for recruitment and selection.	COS - 3. Adoption of artificial intelligence in recruitment and selection saves time and effort related to costs required for recruitment and selection.
N	Valid	95	95	93
	Missing	0	0	2
Mean		4.43	4.44	4.23
Median		5.00	5.00	4.00
Mode		5	5	4
Skewness		-1.539	-1.922	-.636
Std. Error of Skewness		.247	.247	.250

Descriptive statistics were performed on the survey question related to cost-effectiveness of adopting artificial intelligence for recruitment and selection compared to traditional technologies. The mean response was 4.43, indicating that respondents generally agreed that the adoption of AI for recruitment and selection processes is cost-effective. The median response was 5, which further supports the trend of positive responses. The mode was also 5, which means that the most frequent response was "Strongly agree". For better visuals, and to corroborate these statistics, Figure 4.1 below suffices.

Figure 4.1: Cost effectiveness of AI vis-à-vis traditional recruitment and selection strategies



As presented in Figure 4.1, 86.32% of the participants, which represents nearly nine in every 10 participants either somewhat agreed or strongly agreed that adopting AI for recruitment and selection is cost effective than the traditional recruitment and selection techniques.

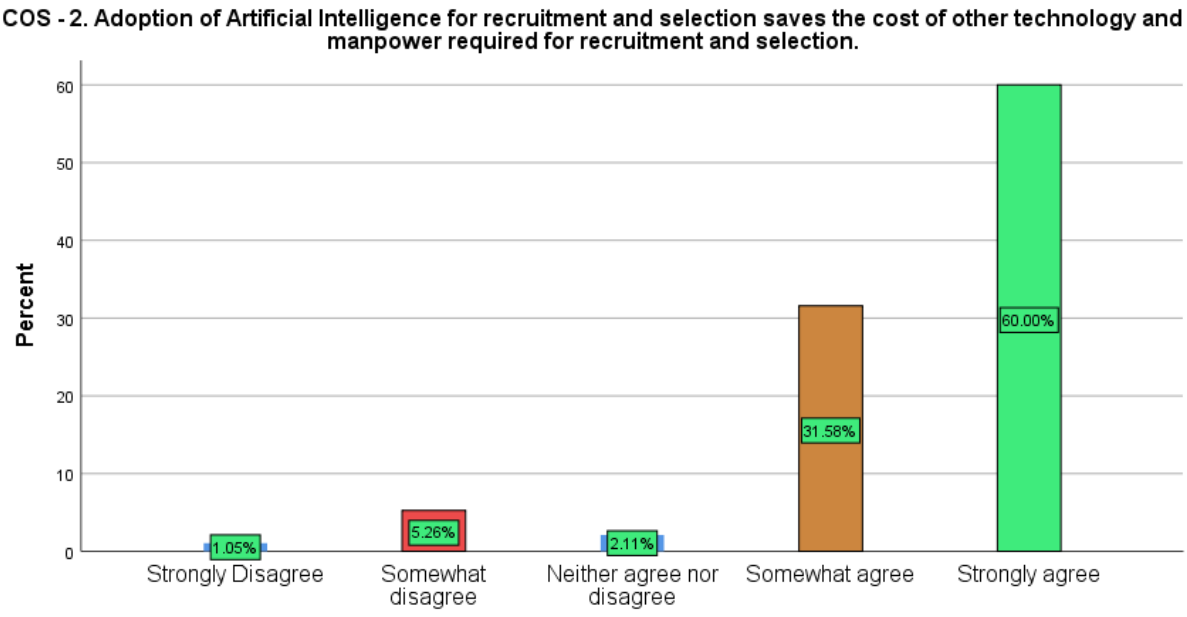
However, the skewness of -1.539 indicates that the distribution of responses is negatively skewed, with a majority of the responses towards the higher end of the scale. This suggests that while there is a general agreement among respondents on the cost-effectiveness of adopting artificial intelligence, there are some who may not agree or may have reservations.

These descriptive statistics provide a preliminary understanding of the responses to the study question related to cost-effectiveness of adopting artificial intelligence for recruitment and selection processes under the technology construct. The mean, median, mode, and skewness provide a comprehensive summary of the responses and highlight the trends and patterns in the data. These statistics can be used as a basis for further

analysis to gain a deeper understanding of the factors influencing AI adoption in recruitment and selection processes among South African universities.

Descriptive statistics were performed on second question relating to the cost-saving benefits of adopting artificial intelligence for recruitment and selection practices in South African universities. The mean response was 4.44, indicating that respondents generally agreed that adopting artificial intelligence saves costs associated with other technologies and manpower required for recruitment and selection processes. The median response was 5, which further supports the trend of positive responses. The mode was also 5, which means that the most frequent response was "Strongly agree". Further, Figure 4.2 provides the visuals to support the claim.

Figure 4.2: Cost-saving benefits of adopting AI



About 91.58% of the participants either somewhat agree or strongly agree that artificial intelligence adoption for recruitment and selection enables cost savings through freeing up resources for other uses.

However, the skewness of the data was -1.922, indicating that the distribution of responses was negatively skewed. This suggests that while there is a general agreement among respondents on the cost-saving benefits of adopting artificial intelligence, there are some respondents who may have disagreed or had reservations.

The third question in this section was related to the time-saving benefits of adopting AI for recruitment and selection processes in South African universities. Attained mean response of 4.23, indicated that respondents generally agreed that adopting artificial intelligence aids efficient use of time and lowers operative expenses needed for recruitment and selection processes. The median response was 4, which further supports the trend of positive responses. The mode was also 4, which means that the most frequent response was "Somewhat agree".

The skewness of the data was -0.636, indicating a relatively symmetrical distribution of responses. This suggests that while there were some variations in responses, overall, the majority of the respondents agreed that adopting artificial intelligence reduces time, human resources practitioner labour need and normal expenses requisite for recruitment and selection processes.

4.3.2. Relative advantage of AI for recruitment and selection

Descriptive statistics were also performed on the survey questions analysing relative advantages of artificial intelligence adoption for recruitment and selection processes in South African universities. The first construct was based on the question which read, ‘Adoption of Artificial Intelligence helps Human Resources Practitioners to select the right candidates.’ The question helped in churning out inferences on the relative advantages of artificial intelligence as a tool for selecting the right candidates. Table 4.4 illustrates the responses to the question.

Table 4.4: The relative advantage of AI as a tool for selecting the right candidates

REA - 4. Adoption of Artificial Intelligence helps Human Resources Practitioners to select the right candidates.

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Strongly Disagree	3	3.2	3.2	3.2
	Somewhat disagree	10	10.5	10.5	13.7
	Neither agree nor disagree	7	7.4	7.4	21.1
	Somewhat agree	38	40.0	40.0	61.1
	Strongly agree	37	38.9	38.9	100.0
	Total	95	100.0	100.0	

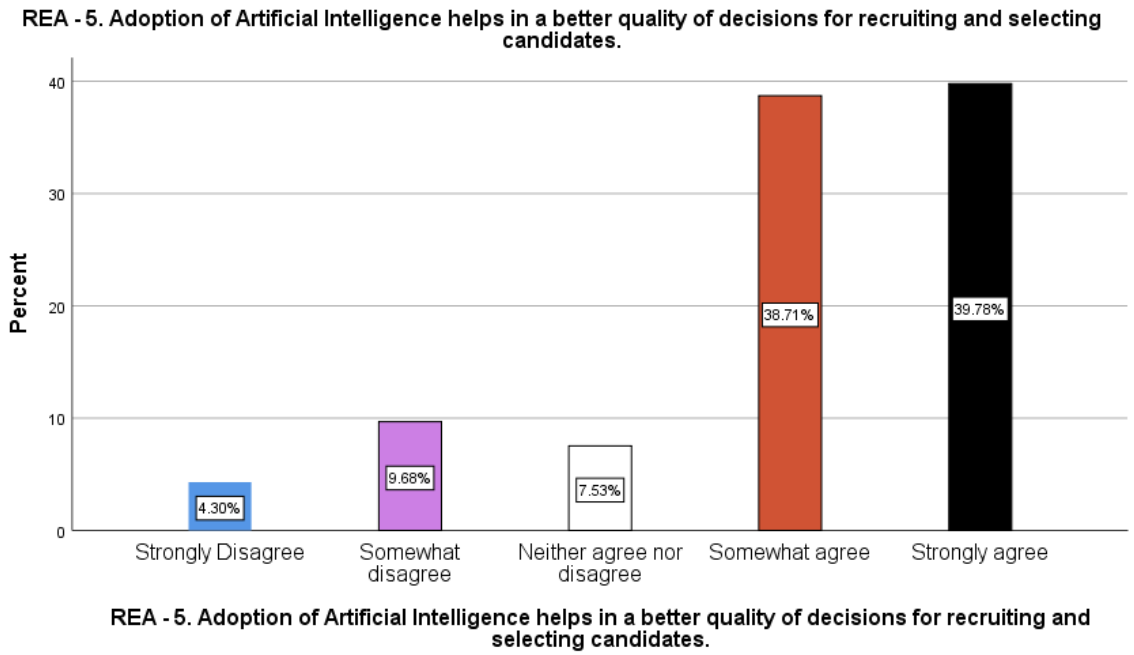
The findings from the analysis of the survey question "Adoption of Artificial Intelligence helps Human Resources Practitioners to select the right candidates" are consistent with previous research that has shown that the use of artificial intelligence in recruitment and selection processes can lead to improved decision-making and candidate selection.

For instance, research by Hunkenschroer and Luetge (2022) found that the utilising AI algorithms in talent sourcing and acquisition processes can improve accuracy and effectiveness in decision-making by reducing biases and subjectivity in the process. Similarly, research by Chen (2022) demonstrated that artificial intelligence can be used to analyse large volumes of data and identify the best candidates for specific roles, leading to improved hiring decisions.

Moreover, the findings from the current analysis align with the theoretical underpinnings of the technology acceptance model (TAM) proposed by Davis (1989) which suggests that users are more likely to accept and adopt a new technology when they perceive it to be useful and easy to use. In the context of recruitment and selection processes, the perceived usefulness of AI in helping to select the right candidates is likely to be a key factor in driving its adoption.

The second question under the subsection was on the role of AI as a tool that enhances better quality of decisions in recruitment and selection practices. Figure 4.3 illustrates the responses from participants.

Figure 4.3: The relative advantage of AI as a decision making tool



The results show that the majority of respondents (78.7%) agreed that adopting artificial intelligence can lead to superior judgements in candidate recruitment and selection, with 39.8% of respondents indicating they strongly agree and 38.7% indicating they somewhat agree.

Conversely, 4.3% of respondents strongly disagreed with the statement, while 9.68% somewhat disagreed and 7.53% neither agreed nor disagreed. These results suggest that the majority of respondents believe that AI adoption can result in better quality decisions in recruitment and selection practices.

The results of this question align with previous studies which have found that the use of artificial intelligence in recruitment and selection can lead to better decision-making outcomes. For example, a study by Pessach, Singer and Avrahami, (2020) found that the

use of predictive analytics in recruitment and selection can lead to better quality decisions by reducing biases and errors that are often present in human decision-making.

Additionally, research by Pessach, *et al.,* (2020) highlighted the importance of using machine learning algorithms to analyse large data sets in recruitment and selection processes, which can help identify patterns and insights that may not be immediately apparent to human recruiters.

The survey question that followed was on the effect of AI on recruitment decisions and actions. For this question a mean score of 4.27 was obtained, suggesting that the survey participants, on average, agreed that adopting AI can increase the efficacy of recruitment and selection decisions and actions. A median score was 4 and a mode of 5, were obtained, indicating that the most frequent response was "Strongly Agree". Figure 4.4 illustrates the distribution of the responses.

Figure 4.4: Relative advantage of AI in decision making and actions

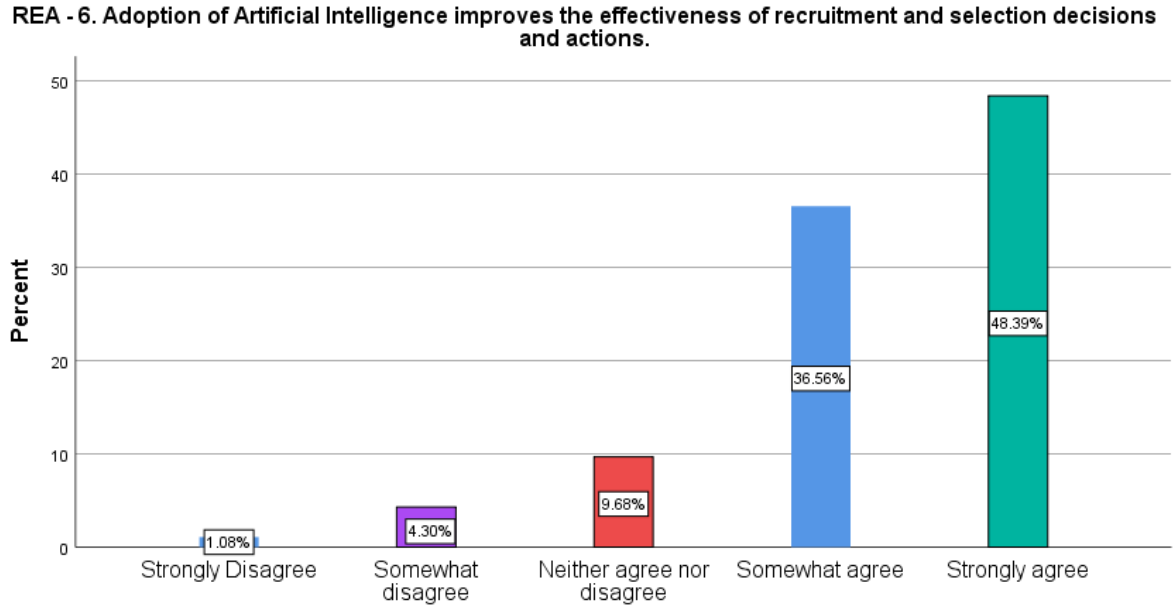


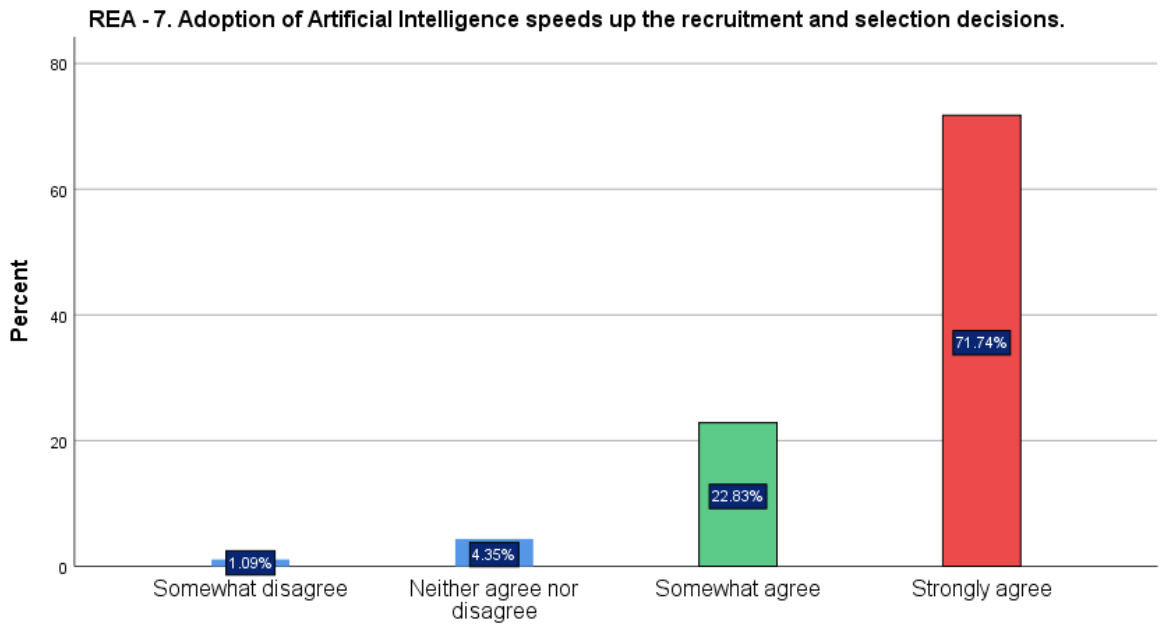
Figure 4.4 illustrates that 48.4% of the respondents strongly agreed that the adoption of AI can enhance proficiency of recruitment and selection decisions and actions, while

36.6% somewhat agreed. Only 1.1% of the respondents strongly disagreed and 4.3% somewhat disagreed with the statement, while 9.7% neither agreed nor disagreed.

The results of this question are consistent with previous research which has suggested that AI can improve the effectiveness of recruitment and selection processes. For example, research by Agrawal, Gans and Goldfarb (2019) found that the use of AI in recruitment and selection processes can lead to improved accuracy and effectiveness of decision-making. Additionally, research by Agrawal, *et al.,* (2019) suggested that AI can improve the efficiency and effectiveness of recruitment and selection processes by reducing the time and resources required to complete these tasks.

Having found that AI supports recruitment and selection practices, the next insight was on relative advantage of artificial intelligence in speeding up recruitment and selection decisions. Analysis provided a mean score for this question as 4.69, showing that participants concurred that adoption of AI can speed up the recruitment and selection decisions. The median score was 5, and the mode was also 5, which suggests that the majority of the respondents chose the highest rating on the scale. Figure 4.5 illustrates the ‘relative advantage’ of artificial intelligence in speeding up the hiring process.

Figure 4.5: The relative advantage of AI in speeding up the recruitment and selection process



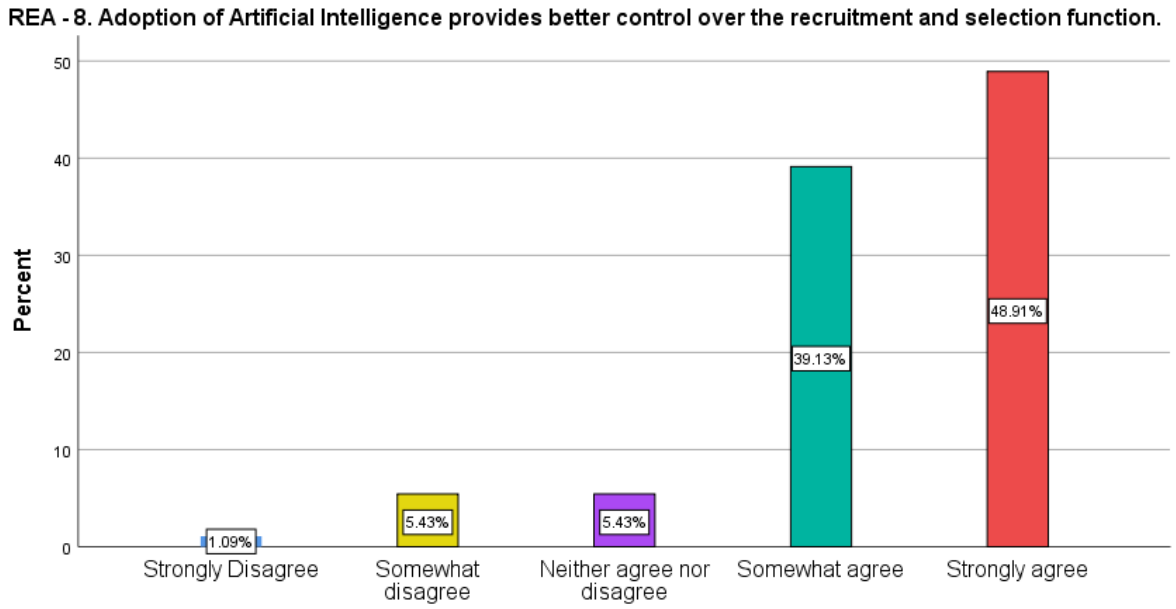
In particular, 71.7% of the respondents strongly agreed that the adoption of AI can speed up the recruitment and selection decisions, while 22.8% somewhat agreed. Only 1.1% of the respondents strongly disagreed and no one chose the "Somewhat Disagree" option, while 4.3% neither agreed nor disagreed.

These results are consistent with the existing literature, which suggests that AI adoption in recruitment and selection practice can significantly accelerate decision-making. For instance, a study by Agrawal, et al., (2019) indicated AI can reduce the amount of time needed for initial screening and shortlisting of candidates, enabling the process to be completed much faster than traditional methods.

In summary, the results of this question indicate that the adoption of AI can have a relative advantage in speeding up the recruitment and selection decisions. This finding may be of particular interest to organizations looking to streamline their recruitment processes and improve their overall efficiency.

After having realised all the relative advantages in adopting artificial intelligence in recruitment and selection processes, it is permissible to conduct an investigation to determine if AI provides better control over the recruitment and selection function. The last question under the relative advantage construct queries if AI adoption provides better control over the recruitment and selection function. Figure 4.6 illustrates the responses.

Figure 4.6: The relative advantage of AI in controlling the recruitment and selection function



REA - 8. Adoption of Artificial Intelligence provides better control over the recruitment and selection function.

The results of the analysis indicate that the majority of the respondents agreed that the adoption of AI can provide better control over the recruitment and selection function. Specifically, 48.91% of the respondents strongly agreed, while 39.13% somewhat agreed. A small percentage of the respondents chose the "Somewhat Disagree" (5.43%) and "Strongly Disagree" (1.09%) options, while 5.43% neither agreed nor disagreed.

These results suggest that the adoption of AI can have a relative advantage in providing control over the recruitment and selection function. By automating various aspects of the process, AI can help ensure consistency and standardization in decision-making,

reducing the risk of human error and bias. It can also provide real-time data and analytics to help organisations make more informed decisions.

These findings are consistent with previous research on the topic of benefits of AI adoption within recruitment and selection. For example, a research by Mehrotra and Khanna (2022) found that AI can enhance the control and transparency of recruitment processes by providing objective and reliable data.

4.3.3. Security and privacy concerns of adopting AI

Adopting AI within recruitment and selection processes has been touted as a means to improve the efficiency and accuracy of candidate selection while minimising the risk of human bias and error. However, concerns have been raised about the security and privacy implications of using AI in this context. Specifically, there are concerns about the potential for breaches of personal data, the accuracy of algorithms used in AI, and the potential for algorithmic bias.

To address these concerns, it is important to understand the extent to which they are perceived as barriers to the AI adoption in recruitment and selection processes. An analysis of data collected from individuals involved in the recruitment and selection processes can help understand this. This part therefore explored descriptive statistics of the constructs related to security and privacy concerns of adopting AI, as measured by the survey questions on the topic was done.

Descriptive statistics were used to summarize the responses of participants to each survey question related to security and privacy concerns. These statistics includes the mean, median, mode, and skewness of the responses, as well as the percentage of participants who chose each response option. The statistics provide insights into the perceived security and privacy concerns associated with artificial intelligence adoption in recruitment and selection processes.

The first question for the construct asked the participants if they do not feel secure with transmitting recruitment and selection data via AI means. Table 4.5 illustrates the responses.

Table 4.5: We do not feel secure with transmitting data via AI

SNP - 9. We feel that recruitment and selection data transmitted in Artificial Intelligence is not secure.

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Strongly Disagree	18	18.9	18.9	18.9
	Somewhat disagree	23	24.2	24.2	43.2
	Neither agree nor disagree	20	21.1	21.1	64.2
	Somewhat agree	22	23.2	23.2	87.4
	Strongly agree	12	12.6	12.6	100.0
	Total	95	100.0	100.0	

The mean score of 2.86 suggests that the majority of the participants somewhat disagree or disagree with the statement that recruitment and selection data transmitted in AI is secure. The median score of 3 and mode score of 2 indicate that the responses are relatively evenly distributed across the 5-point Likert scale.

These findings are consistent with previous research that has identified security and privacy concerns as a key barrier to AI adoption in recruitment and selection processes. The study by Reddy (2022) found that security and privacy concerns are among the key factors that hinder the adoption of AI in human resource management. Additionally, a study by Reddy (2022) noted that the use of AI in recruitment and selection processes has led to concerns about data privacy.

This study findings suggest that security concerns are a significant issue for adopting artificial intelligence in recruitment and selection processes of South African universities.

Further analysis is needed to explore the reasons behind these perceptions and to identify any potential solutions to address these concerns. This could include measures such as improving data encryption, ensuring that data is stored securely, and providing training to HR professionals to help them better understand the security and privacy implications of artificial intelligence in recruitment and selection.

The subsequent question was on the confidentiality and privacy concerns of adopting artificial intelligence. AI adoption in recruitment and selection processes within South African universities has brought up concerns around the confidentiality and privacy of data transmitted and stored by AI. This section focuses on the survey questions related to confidentiality and privacy concerns when adopting AI for recruitment and selection. The descriptive statistics of the constructs are presented below.

Table 4.6: Confidentiality and privacy concerns

SNP - 10. We feel that recruitment and selection data stored and used by Artificial Intelligence lacks in confidentiality and privacy.

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Strongly Disagree	24	25.3	25.3	25.3
	Somewhat disagree	23	24.2	24.2	49.5
	Neither agree nor disagree	13	13.7	13.7	63.2
	Somewhat agree	24	25.3	25.3	88.4
	Strongly agree	11	11.6	11.6	100.0
	Total	95	100.0	100.0	

The mean obtained is 3.06, which illustrates that the participants, in general, are neutral. The median obtained is 3, which further corroborates this claim. Studies have shown that a significant issue in AI adoption in recruitment and selection processes is the concern around the confidentiality and privacy of data transmitted and stored by AI (Reddy, 2022). In the present study, respondents expressed their concern about the lack of confidentiality and privacy of data stored and used by artificial intelligence for recruitment and selection, with the mean score of 3.02. This result is consistent with previous studies that suggest that the use of AI for recruitment and selection raises concerns about data privacy and

security (Reddy, 2022). Respondents also expressed their concern about the possibility of errors due to the algorithms used by AI, with a mean score of 2.74. This finding is also consistent with previous studies that suggest that the use of AI for recruitment and selection raises concerns about transparency and accountability in decision-making Lee, Resnick and Barton (2019). These results suggest that addressing the concerns of confidentiality, privacy, transparency, and accountability is significantly essential for artificial intelligence adoption in recruitment and selection processes of South African universities.

The last question related to the safety concerns in the AI adoption in recruitment and selection practices queried if participants believed that AI was not reliable due to possibility of inaccuracies resulting from algorithms in AI. Figure 4.7 illustrates the responses.

Figure 4.7: Artificial intelligence is not safe due to likely errors algorithms in AI.

Nearly 50% of the participants (46.81%) somewhat agree or strongly agreed that there are some possibilities of errors in the algorithms. The mean score of 2.74 was obtained, which suggests that the majority of the participants somewhat disagree or disagree with

the statement that AI is not safe due to the possibility of error in algorithms. The median score of 3 indicates that responses are evenly distributed across the 5-point Likert scale, with a mode score of 1 suggesting that some participants strongly disagree with the statement.

These findings are in line with previous research that has identified concerns about the reliability and accuracy of artificial intelligence algorithms imbedding within the recruitment and selection processes. A study by Votto, Valecha, Najafirad and Rao, (2021) found that the use of AI in recruitment and selection processes raises concerns about fairness, accuracy, and bias. Additionally, a study by Mikalef and Gupta (2021) noted that there are concerns about the reliability of AI algorithms in decision-making.

The findings from this study suggest that safety concerns are not a significant barrier to artificial intelligence adoption in recruitment and selection processes of South African universities. However, it is important to note that concerns about algorithmic bias and accuracy may still be present and should be addressed through careful algorithm design, testing, and ongoing monitoring to ensure that the use of AI in recruitment and selection processes is fair, accurate, and transparent. Further analysis is needed to explore these concerns and to identify any potential solutions to address them.

4.3.4. Human Resources Readiness for AI adoption

The readiness of human resources is critical for successfully adopting AI in recruitment and selection processes among universities. Adoption of artificial intelligence requires certain skills and knowledge in the field of HR, such as data analysis and interpretation, understanding of algorithms, and familiarity with software and technology. Therefore, assessing the human resources readiness in adopting AI is crucial for understanding the barriers and opportunities for implementing the technology effectively. Table 4.7 illustrates the descriptive statistics obtained from questions on the human resources readiness construct.

Table 4.7: Human Resources Readiness Constructs

Statistics

		HRR- 12. Human Resources department has financial budget to adopt artificial intelligence for recruitment and selection.	HRR - 13. Human Resources department personnel are expert to use artificial intelligence for recruitment and selection.	HRR - 14. Human Resources leaders in universities are willing to invest in artificial intelligence for recruitment and selection.
N	Valid	95	94	95
	Missing	0	1	0
Mean		3.15	2.80	3.38
Median		3.00	3.00	3.00
Mode		4	2	3
Skewness		-.333	.170	-.253
Std. Error of Skewness		.247	.249	.247

To address the research question on the factors influencing AI uptake of AI in recruitment and selection processes within South African universities, the study investigated several factors, including the readiness of human resources departments in universities to adopt AI for recruitment and selection. The results showed that the human resources department has a moderate financial budget to adopt AI for recruitment and selection, as evidenced by a mean score of 3.15. However, the department personnel had a relatively lower mean score of 2.8, indicating that they may not be adequately prepared to use AI for recruitment and selection. Nonetheless, the human resources leaders in universities got a greater mean of 3.38, signifying a willingness to invest in AI for recruitment and selection.

The study findings are consistent with previous literature that has highlighted the importance of human resources readiness in the successful adoption and implementation of artificial intelligence in recruitment and selection processes (Hamouche, 2021; Ore and Sposato, 2021; Votto, et al., 2021). Specifically, the literature suggests that the readiness of human resources departments in universities can be a crucial AI adoption success

determinant for recruitment and selection (Davenport & Ronaki, 2018). The readiness of human resources departments can be measured by various factors, such as the availability of financial resources, the expertise of personnel in using AI technologies, and the support of human resources leaders in the organisation (Hamouche, 2021).

In summary, the findings suggest that while human resources departments in universities have a moderate financial budget to adopt AI for recruitment and selection, personnel may not be adequately prepared to use AI. However, the willingness of human resources leaders to invest in AI for recruitment and selection indicates the potential for effective AI adoption and successful future implementation. Therefore, it is essential for universities to focus on enhancing the readiness of human resources departments by investing in the necessary training and development programs for personnel and providing the required financial resources to enable successful adoption of AI in talent acquisition processes.

4.3.5. Top Management Support for AI adoption

Adopting AI for recruitment and selection is a complex and multidimensional process that requires the support and commitment of various stakeholders within an organization, including top management. Top management support has been identified as a critical success factor for the adoption of new technologies such as AI. The purpose of this subsection is to examine the influence of top management support for the artificial intelligence adoption for recruitment and selection in South African universities, using three survey questions. The responses to the three questions are presented in Table 4.8.

Table 4.8: Descriptive Statistics: Top Management Support for the adoption of AI

Statistics

		TMS - 15. Top management provide support for the adoption of artificial intelligence for recruitment and selection.	TMS - 16. Top management offer funds for adoption of artificial intelligence for recruitment and selection.	TMS - 17. Top management knows the benefits of adoption of artificial intelligence for recruitment and selection.
N	Valid	95	95	92
	Missing	0	0	3
Mean		3.52	3.34	3.70
Median		4.00	3.00	4.00
Mode		4	4	4
Skewness		-.403	-.191	-.658
Std. Error of Skewness		.247	.247	.251

The first question queried if the top management provided assistance for adoption of artificial intelligence for recruitment and selection. The 3.52 mean score obtained for this question, implied that study participants felt that top management provided some level of support for the adoption of AI. The median and mode scores were both 4, suggesting that many respondents agreed that top management support was present. However, the negative skewness (-0.403) indicates that there were some respondents who disagreed or strongly disagreed with this statement.

The secondly question was on the top management's readiness to avail funds in support or financing of artificial intelligence adoption in talent acquisition drive. A mean score of 3.34 was attained for this question, inferring that respondents felt that top management offered some financial support for the adoption of AI. The mode score was 4, suggesting that many respondents agreed that financial support was present. However, the negative skewness (-0.191) indicates that there were some respondents who disagreed or strongly disagreed with this statement.

The third concern was assessing if, the top management knew the benefits of artificial intelligence adoption for recruitment and selection. The mean score of 3.7 was obtained

for the question, conveying that participants felt that top management had some knowledge of AI adoption advantages and benefits for recruitment and selection. The median and mode scores were both 4, suggesting that many respondents agreed that top management had knowledge of the benefits of AI. However, the negative skewness (-0.658) indicates that there were some respondents who disagreed or strongly disagreed with this statement.

The importance of top management support for the successful adoption of new technologies such as AI has been extensively discussed in the innovation adoption literature. One relevant theoretical framework is the Technology Acceptance Model (TAM), which posits that the perceived usefulness and ease of use of a technology influence its adoption, and that these perceptions are influenced by various factors, including organisational and social contexts (see Mikalef &Gupta, 2021). In the context of AI adoption, top management support can play a crucial role in shaping these perceptions by providing resources, reducing uncertainty, and promoting positive attitudes towards the new technology (Mikalef & Gupta, 2021).

Moreover, the Resource-Based View (RBV) of the firm suggests that the availability and allocation of resources are critical for the adoption of new technologies, and that top management play a key role in this process (Srivastava, Fahey & Christensen, 2001). Within the context of artificial intelligence adoption for recruitment and selection, top management support can influence the level of financial and human resources allocated to the adoption process, as well as the degree of involvement and participation of different stakeholders in the process (Rodgers, Murray, Stefanidis, Degbey & Tarba, 2023).

In summary, literature suggests that top management support is a critical factor in the adoption of new technologies such as AI for recruitment and selection. The results of the survey highlight the need for South African universities to prioritise building awareness and knowledge among top management, securing adequate financial resources, and creating a supportive organisational culture that encourages experimentation and learning.

4.3.6. Competitive Pressure to adopt AI

As the adoption of artificial intelligence (AI) becomes more widespread, it is important for universities to consider the competitive pressure they may face to adopt these technologies for recruitment and selection. Within this sub-section, descriptive analysis of responses to three questions related to competitive pressure to adopt AI for recruitment and selection in South African universities is provided. The questions cover the pressure from competitors' AI adoption, the influence of recruitment and selection practices in other universities, and the monitoring of competitors' AI use for recruitment and selection.

Through the analysis of these responses, we can gain insights into the level of competitive pressure faced by South African universities in adopting AI for recruitment and selection, as well as the potential impact of such pressure on adoption decisions. Drawing upon relevant literature contextualises the results and highlight their implications. Table 4.9 illustrates the descriptive statistics of the responses.

Table 4.9: Descriptive Statistics: Competitive pressure to adopt AI

Statistics

		COM - 18. Our university has pressure of adoption of Artificial Intelligence for recruitment and selection due to competitors' adoption of artificial intelligence for recruitment and selection.	COM - 19. Recruitment and Selection practice across universities forced us to adopt artificial intelligence for recruitment and selection.	COM- 20. Our university keeps a watch on competitors for the artificial intelligence technology used for recruitment and selection.
N	Valid	95	95	95
	Missing	0	0	0
Mean		3.62	3.46	3.49
Median		4.00	4.00	3.00
Mode		3[a]	3	3
Skewness		-.510	-.309	-.419
Std. Error of Skewness		.247	.247	.247

a. Multiple modes exist. The smallest value is shown

The results of the survey indicate that South African universities feel a moderate level of pressure to adopt AI for recruitment and selection. The mean score for question 1, "Our university has pressure of AI adoption due to competitors' adoption of AI for recruitment and selection" was 3.62, which suggests that universities feel some pressure to adopt AI due to the adoption of AI by their competitors.

Similarly, question 3, “Our university keeps watch on competitors for the artificial intelligence technology used for recruitment and selection" received a mean score of 3.49, indicating that universities are paying attention to their competitors' adoption of AI in recruitment and selection.
Question 2, "Recruitment and selection practice across universities forced us to adopt artificial intelligence for recruitment and selection" received the mean score of 3.46, suggesting that universities feel a moderate level of pressure to adopt AI due to the recruitment and selection practices of other universities.

The literature has consistently highlighted the importance of competitive pressure in driving organisations to adopt new technologies. The results of the survey suggest that South African universities are experiencing a moderate level of competitive pressure to adopt AI for recruitment and selection. The pressure is mainly driven by AI adoption by competitors in their recruitment and selection practices, and the monitoring of other universities in their utilisation of artificial intelligence enhanced technology in recruitment and selection.

4.3.7. Support from technological vendors to adopt AI in the recruitment and selection processes

This section examined the extent to which technological vendors provide support for artificial intelligence adoption in recruitment and selection among South African universities. The adoption of AI in recruitment and selection requires adequate support from technological vendors, including training, technical support, and continuous assistance. This section analyses the responses to three survey questions that assess the level of support provided by technological vendors to universities in South Africa for

AI adoption in recruitment and selection. Table 4.10 illustrates the descriptive statistics highlighting the support from the technological vendors.

Table 4.10: Descriptive Statistics: Support from technological vendors

Statistics

		STV- 21. Artificial Intelligence training is fairly provided by the vendors of artificial intelligence for recruitment and selection.	STV - 22. Artificial Intelligence vendors provide adequate technical support during implementation of artificial intelligence for recruitment and selection.	STV - 23. Artificial Intelligence vendors provide adequate technical support after implementation of artificial intelligence for recruitment and selection.
N	Valid	95	94	94
	Missing	0	1	1
Mean		3.60	3.70	3.66
Median		4.00	4.00	4.00
Mode		3	4	3
Skewness		-.281	-.088	-.320
Std. Error of Skewness		.247	.249	.249

From the first question, the mean response of 3.60 and median response of 4 indicate that the respondents had a slightly positive perception of the support provided by technological vendors for AI adoption in recruitment and selection. However, a mode of 3 suggests that a significant number of respondents had a neutral perception on the issue. The skewness value of -0.281 indicates a slight negative deviation from the normal distribution. The second question recorded a mean response of 3.7 and a median response of 4 which both indicate that the respondents generally had a positive perception of the training provided by technological vendors for AI adoption in recruitment and selection. A mode of 4 suggests a relatively large number of participants strongly agreed with the assertion.

The skewness value of -0.088 indicates a nearly symmetrical distribution. The last question had a mean response of 3.66 and median response of 4 indicate that the

respondents had a slightly positive perception of the continuous support provided by technological vendors for AI adoption in recruitment and selection. However, a mode of 3 suggests that a significant number of respondents had a neutral perception on the issue. The skewness value of -0.32 indicates a slight negative deviation from the normal distribution.

Overall, the analysis suggests that while the respondents generally had a positive perception of the support provided by technological vendors for artificial intelligence adoption in recruitment and selection, there were significant numbers of respondents who had a neutral perception on the issue. This indicates that there may be room for improvement in the level of support provided by technological vendors, particularly in areas such as adequate support and continuous support. The literature suggests that effective support from technological vendors can be critical for the successful adoption of new technologies such as AI, as it can help to address technical challenges, build capacity, and ensure sustainability (Liu, et al., 2021; Wang & Li, 2020). Therefore, organisations seeking to adopt AI for recruitment and selection should prioritize building strong partnerships with technological vendors, setting clear expectations and standards for support, and regularly evaluating the effectiveness of the support provided.

4.3.8. Support from government in adopting AI in the recruitment and selection processes

The adoption of artificial intelligence in recruitment and selection in universities can be influenced by different factors, including the support received from the government. The government can provide support in terms of understanding the need for AI, providing necessary funds for implementation through the Department of Higher education and Training and other entities. In this section, descriptive statistics from the survey questions that sought to establish the magnitude of government support that universities in South Africa receive is provided. Table 4.11 illustrates the descriptive statistics on the level of support from the government to adopt AI in the recruitment and selection processes.

Table 4.11: Descriptive Statistics: Level of support from the government to adopt AI in the recruitment and selection processes

Statistics

		SFG - 24. The Government understands the need for adoption of artificial intelligence for recruitment and selection in universities.	SFG- 25. The Government through the Department of Higher Education and Training and other entities supports the implementation of artificial intelligence for recruitment and selection.	SFG - 26. The Government offer funds for the adoption of artificial intelligence for recruitment and selection in universities.
N	Valid	94	94	94
	Missing	1	1	1
Mean		3.13	3.21	2.79
Median		3.00	3.00	3.00
Mode		4	3	3
Skewness		-.211	-.206	.108
Std. Error of Skewness		.249	.249	.249

For the first question, the mean score was 3.13, indicating that respondents are relatively neutral about whether the government understands the need for AI adoption for recruitment and selection in universities. A median score of 3 and mode score of 4 suggest that a significant proportion of respondents neither agree nor disagree with the statement. The skewness score of -0.211 indicates a relatively symmetrical distribution of responses.

On the second question, the mean score was 3.21, indicating that respondents are relatively neutral about whether the government through the Department of Higher education and Training and other entities supports the implementation of AI for recruitment and selection. The median score of 3 and mode score of 3 suggest that a significant proportion of respondents neither agree nor disagree with the statement. The skewness score of -0.206 indicates a relatively symmetrical distribution of responses.

On the last question, the mean score was 2.79, indicating that respondents disagreed that the government offers funds for adopting AI of AI for talent acquisition practices in universities. A median score of 3 and mode score of 3 suggest that a significant proportion of respondents disagreed with the statement. The skewness score of 0.108 indicates a slightly skewed distribution of responses towards the left side.

In general, the results suggest that universities in South Africa do not receive significant support from the government in terms of the AI adoption for recruitment and selection. The neutral responses in the first two questions suggest that there is a lack of clarity or awareness of the government's stance on this issue. The negative response in the third question suggests that universities may need to explore alternative sources of funding for AI adoption for recruitment and selection.

4.4. Statistical test: Partial Least Squares-Structural Equation Modelling

To fully address the study hypotheses, the researcher performed the Partial Least Squares-Structural Equation Modelling (PLS-SEM) using the Smart-PLS 4 software. While there were a number of options at the researcher's disposal, such as multiple regression, PLS-SEM was selected over its advantages over other methods. For instance, PLS-SEM has the ability to simultaneously examine multiple relationships within a model, measure latent variables, handle measurement errors, and incorporate both the observed and the latent variables (Nachtigall, et al., 2003).

PLS-SEM is a powerful multivariate analysis technique that allows researchers to evaluate complex causal relationships and make predictions based on data. PLS-SEM is particularly useful when the data has many variables and there is uncertainty about the underlying causal structure of the variables. The PLS-SEM involved two main stages: the measurement model and the structural model. In the measurement model, the researcher created a set of constructs, which are groups of related variables that represent abstract concepts. The relationships between the constructs and their constituent variables were then examined using the factor analysis.

The path coefficient from the structural model is presented in Table 4.12.

Table 4.12: Path Coefficient Output from SmartPLS4

Hypothesis	Hypothesis path	Path coefficient	*t*-statistics
1.Cost Effectiveness (COS) of Artificial intelligence (AI) for Recruitment and Selection (RS) will positively affect the adoption (ADP) of artificial intelligence for Recruitment and Selection (RS).	COS → ADP	0.352	3.751***
2.Relative advantage (REA) of Artificial Intelligence (AI) for Recruitment and Selection (RS) will positively affect Adoption (ADP) of Artificial Intelligence (AI) for Recruitment and Selection (RS)	REA → ADP	0.173	2.074**
3. Security and Privacy Concerns (SNP) in Artificial Intelligence negatively influence the Adoption (ADP) of Artificial Intelligence (AI) for Recruitment and Selection (RS)	SNP → ADP	-0.408	4.133***
4. Human Resources Readiness (HRR) positively influences the Adoption (ADP) Artificial Intelligence (AI) for Recruitment and Selection (RS)	HRR → ADP	0.406	2.514**
5. Top Management Support (TMS) positively influences the Adoption (ADP) Artificial Intelligence (AI) for Recruitment and Selection (RS).	TMS → ADP	0.343	4.552***
6. Competitive Pressure (COM) positively influences the Adoption (ADP) Artificial Intelligence (AI) for Recruitment and Selection (RS).	COM → ADP	0.200	3.421**
7. Support from Technology Vendors (STV) positively influences the Adoption (ADP) Artificial Intelligence (AI) for Recruitment and Selection (RS	STV → ADP	0.107	4.801***
8. Support from Government (SFG) positively influences the Adoption (ADP) Artificial Intelligence (AI) for Recruitment and Selection (RS)	SFG → ADP	0.276	3.757***
t-values at 5% sig level =1.96**; at 1% sig level = 2.58***			

These hypotheses propose a set of relationships between different constructs related to artificial intelligence (AI) adoption for recruitment and selection (RS) in South African universities.

Hypothesis 1 proposes that the cost-effectiveness of AI for RS has a positive effect on the adoption of AI for RS. This hypothesis is supported by a significant positive path coefficient (0.352) and t-statistics (3.751). This suggests that universities that perceive AI as a cost-effective option for RS are more likely to adopt it.

Hypothesis 2 proposes that the relative advantage of AI for RS has a positive effect on the adoption of AI for RS. This hypothesis is also supported by a significant positive path

coefficient (0.173) and t-statistics (2.074), indicating that universities that perceive AI as having relative advantages for RS are more likely to adopt it.

Hypothesis 3 proposes that security and privacy concerns in AI negatively influence the adoption of AI for RS. This hypothesis is supported by a significant negative path coefficient (-0.408) and t-statistics (-4.133), indicating that universities that perceive AI as having security and privacy concerns are less likely to adopt it.

Hypothesis 4 proposes that human resources readiness positively influence the adoption of AI for RS. This hypothesis is supported by a significant positive path coefficient (0.406) and t-statistics (2.514), suggesting that universities with higher levels of human resources readiness are more likely to adopt AI for RS.

Hypothesis 5 proposes that top management support positively influence the adoption of AI for RS. This hypothesis is supported by a significant positive path coefficient (0.343) and t-statistics (4.552), indicating that universities with higher levels of top management support are more likely to adopt AI for RS.

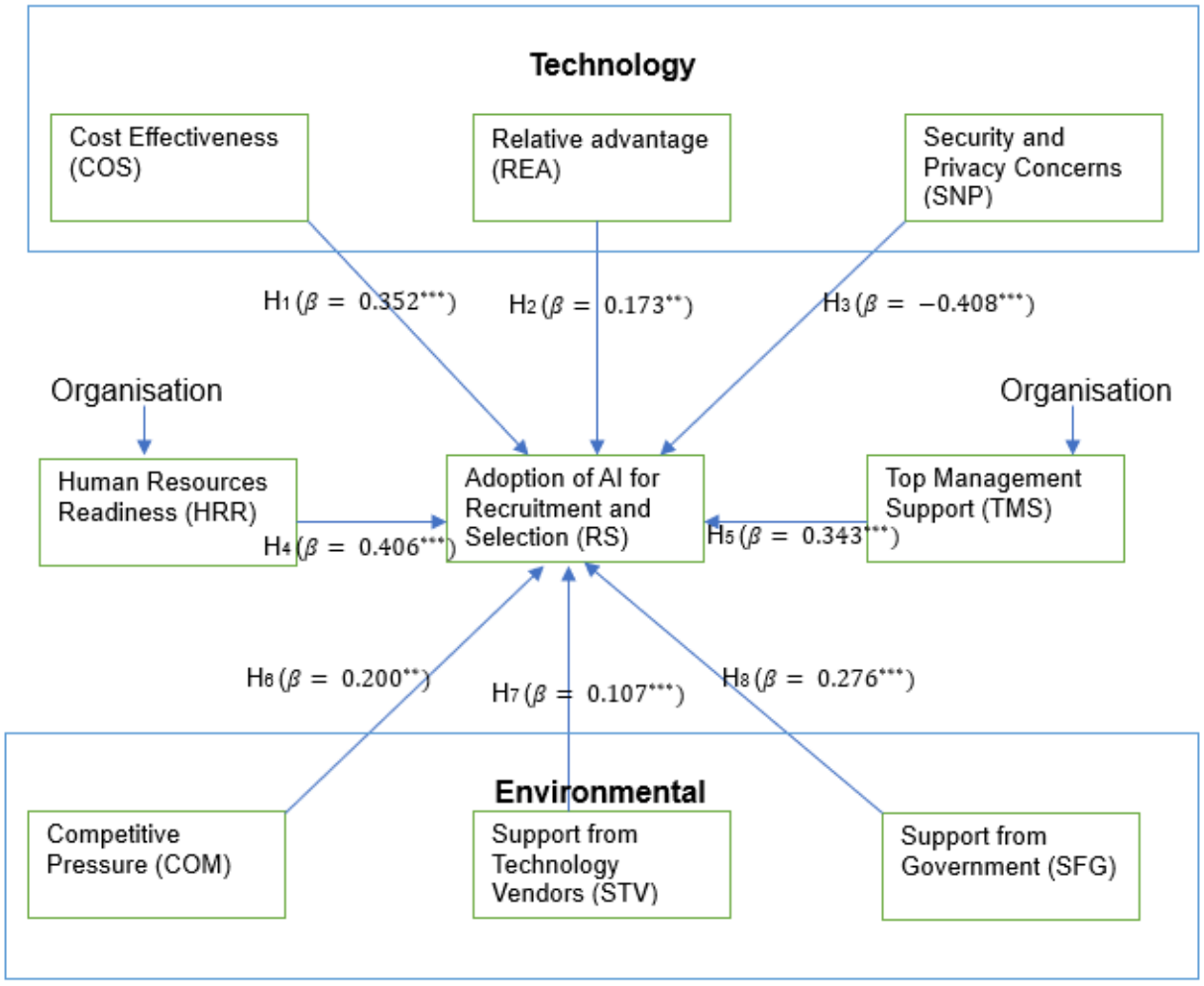
Hypothesis 6 proposes that competitive pressure positively influence the adoption of AI for RS. This hypothesis is supported by a significant positive path coefficient (0.200) and t-statistics (3.421), indicating that universities that face competitive pressures to adopt AI for RS are more likely to adopt it.

Hypothesis 7 proposes that support from technology vendors positively influence the adoption of AI for RS. This hypothesis is supported by a significant positive path coefficient (0.107) and t-statistics (4.801), indicating that universities with higher levels of support from technology vendors are more likely to adopt AI for RS.

Hypothesis 8 proposes that support from the government positively influence the adoption of AI for RS. This hypothesis is supported by a significant positive path coefficient (0.276) and t-statistics (3.757), suggesting that universities with higher levels of government support for AI adoption for RS are more likely to adopt it.

In addition to the information presented in Table 4.12, Figure 4.8 also illustrates the structural model mapping the relationships.

Figure 4.8: Structural Model mapping the relationships



In conclusion, the PLS-SEM analysis provides support for the majority of the proposed hypotheses, highlighting the importance of different factors such as cost-effectiveness, relative advantages, top management support, and competitive pressure in driving the adoption of AI for RS in South African universities. These findings are consistent with previous research on technology adoption in organizations and have important implications for universities seeking to adopt AI for RS.

4.5. Research findings

This section presents the results of the statistical tests conducted in the study, including descriptive statistics and PLS-SEM, and their connection to the research questions. The main objective was to determine the factors influencing AI adoption in the recruitment and selection processes of South African universities. Descriptive statistics revealed that these universities are not hesitant to adopt AI in their recruitment processes.

The second research question focused on the factors that influence AI adoption in these processes. The PLS-SEM analysis indicated as in the study by Pillai and Sivathanu (2020), ‘that cost effectiveness, relative advantages of AI, top management support’, competitive pressure, support from technology vendors, and support from government have a positive impact on AI adoption. Conversely, security and privacy concerns negatively affect the adoption of AI.

Based on the findings from the statistical analysis, the following strategies could be considered to enhance Artificial Intelligence (AI) adoption in recruitment and selection in South African universities:

Emphasising the cost-effectiveness of AI in recruitment and selection. Organisations can promote the cost savings associated with AI adoption by highlighting the reduced need for other technology and manpower, which can help to convince decision-makers to invest in AI.

Highlighting relative advantages of artificial intelligence for recruitment and selection, organisations can focus on derived benefits of AI in recruitment and selection, such as faster decision-making, improved quality of decisions, and better control over the talent acquisition practices to persuade stakeholders to adopt AI.

Addressing security and privacy concerns; institutions can address concerns related to the security and privacy of data generated from recruitment and selection transmitted through AI by implementing secure data management protocols and training staff to follow best practices for data privacy.

Improving human resources readiness. Organisations can ensure that their human resources department has the necessary resources, skills, and training to effectively adopt and use AI for recruitment and selection.

Securing top management support, organisations can prioritise building awareness and knowledge among top management, securing adequate financial resources, and creating a supportive organizational culture that encourages experimentation and learning to secure top management support for AI adoption.

Responding to competitive pressures, organisations can monitor and respond to competitive pressures related to AI adoption by keeping abreast of the latest AI technologies and trends in recruitment and selection, and by ensuring that they are up-to-date with the latest best practices in the field.

Leveraging support from technology vendors and the government, organisations can work closely with technology vendors and government agencies to secure the necessary financial resources, training, and technical support for effective adoption and utilisation of artificial intelligence for recruitment and selection.

4.6. Conclusion

In conclusion, this chapter has presented the findings of a study on artificial intelligence (AI) adoption of for recruitment and selection in South African universities. Descriptive statistics indicated that the universities were generally receptive to artificial intelligence adoption of AI in their hiring processes. The PLS-SEM analysis identified several factors that positively impacted AI adoption, including cost effectiveness, relative advantages of AI over traditional methods, top management support, competitive pressure, support from technology vendors, and support from the government. On the other hand, privacy and security concerns had a negative affect on AI adoption. Drawn perceptions from this research can give guidance to universities and other organisations in their decision-making processes related to the AI adoption in recruitment and selection processes.

CHAPTER 5: CONCLUSION AND RECOMMENDATIONS

5.1. Introduction

Artificial intelligent technology (AI) use in recruitment and selection processes has been gaining popularity in recent years. The research purpose was to establish factors influencing adoption of Artificial Intelligence in recruitment and selection processes among South African universities and consequently recommend feasible strategies of adopting AI in recruitment and selection processes of the universities. The research questions that guided the enquiry were: (1) What factors influence adoption of artificial intelligence in recruitment and selection processes among South African universities?; (2) What is the relationship between the cost effectiveness of artificial intelligence for recruitment and selection and the adoption of artificial intelligence for recruitment and selection?; (3) Does the relative advantage of artificial intelligence for recruitment and selection affect the adoption of artificial intelligence for recruitment and selection?; and (4) What strategies can be considered to enhance adoption of artificial intelligence in recruitment and selection among South African universities? To answer these questions, a survey was conducted among human resource practitioners in South African universities, and the data was analysed using descriptive statistics and partial least squares-structural equation modelling (PLS-SEM). This chapter provides summary of findings, the implication of the research and limitations and future research.

5.2. Summary of the findings

The findings from the descriptive statistics and PLS-SEM analysis reveal that South African universities are not hesitant in adopting AI in their recruitment processes. The factors that positively impact AI adoption include cost-effectiveness, relative advantages of AI over traditional methods, top management support, competitive pressure, support from technology vendors, and support from the government. On the other hand, security and privacy concerns have a negative impact on the adoption of AI. These findings provide important insights into the current state of AI adoption in South African universities and the factors that influence its adoption. The findings are similar to a comparative study done by Pillai and Sivathanu (2020) revealed that cost effectiveness, relative advantage,

top management support, HR readiness, competitive pressure and support from AI vendors have an encouraging effect on adoption while conversely, security and privacy concerns had an adverse effect on adopting AI the adoption in talent sourcing.

5.3. Implications of the findings and policy action plans

The findings of this study have several practical and theoretical implications. The practical implications of the study substantiate that artificial intelligence adoption within recruitment and selection processes can lead to cost-effectiveness, time-saving, and better-quality hiring decisions. HR staff are better guided in AI technology required for recruitment and selection (Pillai & Sivathanu, 2020). However, concerns about privacy and security including Algorithms flaws should be resolved to guarantee effective implementation of AI. As Pillai and Sivathanu (2020) also alluded, theoretical implications of this study suggest that factors such as relative advantage, top leadership support, adoption pressure from competitors, technology vendor backing, sponsorship from government, and human capital practitioner readiness have critical functions in the adoption of AI.

Potential benefits of AI adoption in recruitment and selection are numerous. The role of artificial intelligence in human resources management is said to be ‘emerging’ (Vanderbist, 2020). The research has indicated more vividly the factors that are likely to influence the adoption of AI in talent hiring process among the institutions universities. Talent management as Chen (2022) highlights, must be carried out carefully and systematically to achieve the organisations goals. It is therefore imperative for universities to tailor AI adoption according to the requirement of their environment.

Chen (2022) cites Black and Esch (2020b) who identified six recruitment and selection activities of ‘job advertising, job search, application, selection, assessment, and coordination’ where AI recruitment tools are generally utilised. AI can help to identify the most qualified candidates, reduce bias in the recruitment process, and automate repetitive tasks (Vanderbist, 2020). According to Chen (2022) candidates passive to the job market can be reached through AI. Investment in an AI tool can expose the university in ‘external channels’ effective in passive candidate recruitment (Chen, 2022). Moreover,

AI can lead to faster and more accurate decision-making, improving the overall efficiency of the talent acquisition process and impartial succession planning (Vanderbist, 2020).

Nonetheless, the challenges of adopting artificial intelligence in the recruitment and selection include the high cost of implementation, as Chen (2022) notes, some AI tools can bring excessive costs and a plausible recommendation is to inexpensively implement AI recruitment and selection tools in phases. Black and Gregersen (2013) are cited by Chen (2022) noting that organisations intending on a large-scale adoption of AI in recruitment have to exercise caution because studies have demonstrated that 60 to 80% entities that embark on 'large scale digital transformational changes suffer economic setbacks'. It also critical as Pillai and Sivathanu (2020) recommends institutions to critically contemplate the AI technology for execution of recruitment and selection functions aligned to the overall strategy.

Concerns about data privacy and security are another challenge that requires a strategic imperative. The Protection of Personal Information (POPI) Act, was promulgated in 2013 (Privett, 2021). POPI has a huge impact on recruitment, especially the storage of candidate personal data which most AI tools are premised on. Chen (2022) rightfully informs that to develop artificial intelligence for recruitment decisions, huge amounts of data has to be collected from a number of sources. Vanderbist (2020) points that data availability and candidate consent for a company to use, can be an AI barrier since AI systems are reliant of substantive datasets and data processing. An additional challenge is the storage and safekeeping of data (Vanderbist, 2020). The use of such data may have legal ramifications and privacy issues as put by (Chen (2022) quoting Chichester Jr and Giffen (2019). As an emerging technology, regulation and laws governing AI might also be in their infancy. Government policy should be aligned with such changes. Universities and AI vendors should ensure compliance with the legal requirements of data management (Chen, 2022).

The human resources component especially the need for specialised skills and the perceived threats on human resource practitioners roles could be a challenge. The study demonstrated that Human resources readiness is critical for adoption (Vanderbist, 2020).

Chen (2022) believes there is a misconception of AI tools replacing the human workforce. AI aids the human workforce by doing the mundane and repetitive work but does not yet possess the ability to conduct such activities as understanding cultural fit (Chen, 2022; Pillai & Sivathanu, 2020). According to Vanderbist (2020), there is a fear among human resources practitioners of losing control over the process and of being made redundant by AI. The fear is also shared by Ore and Sposato (2021) who indicate the cynicism human resources practitioners have due to apprehensiveness of losing their jobs. However, Vanderbist (2020) acknowledges that although AI seem disruptive initially, the end result is ideal. Parts of society may lose jobs for a period, but the end result might be a net jobs gain (Vanderbis, 2020), citing (Lexa, 2017). Specialised skills are essential to ensure human resources practitioners are aware of the AI input such as algorithms to ensure alignment to strategies (Weinstein, 2012) as quoted by (Chen, 2022). Perhaps the main weakness in AI is found within the datasets and the algorithm utilised for decision making. Accordingly, as Vanderbist (2020), concludes, employees will have to be trained as much as possible to embrace the novel technology.

To enhance the technological adoption in the hiring process, universities should develop supportive organizational culture that promotes innovation and experimentation. Policymakers should provide adequate resources and support for the adoption of AI, including training for staff and addressing privacy and security concerns. Additionally, practitioners should be open to the benefits of AI and willing to adapt to the changing recruitment and selection landscape. Within their competitive landscape individual universities will have to embrace AI as soon as possible to guarantee competitiveness and as Vanderbist (2020) puts it, those not adopting AI will be left behind by the those who adopt it early, a form of first mover advantage with ‘enormous competitive advantage’.

In conclusion, the findings of this study provide valuable insights into the factors that influence the AI adoption in recruitment and selection processes of the South African universities. The practical and theoretical implications of this study highlight the importance of considering the various factors that impact AI adoption and provide

recommendations for universities, policymakers, and practitioners to enhance such technological adoption.

5.4. Limitations and Recommendations for Future Research

Despite the valuable insights gained from this study, there were certain limitations that need to be acknowledged. One limitation is that the study focused solely on South African universities, and the findings may not be generalizable to other contexts. Another limitation is the reliance on self-reported data from HR professionals, which may be akin to a social desirability bias and inaccuracies in recall. Additionally, the study did not explore the ethical and legal implications of adopting artificial intelligence in recruitment and selection, which can be a worthwhile future research area.

In terms of future research, it would be useful to conduct a longitudinal study to assess the long-term impact of AI adoption on recruitment and selection outcomes. This could involve tracking the performance and retention rates of employees recruited using AI versus traditional methods over an extended period. Another area for future research could be to investigate the impact of different types of AI algorithms on recruitment and selection outcomes, as well as the perceived fairness and bias of these algorithms.

Furthermore, it would be valuable to discover the bearing of AI adoption on HR related processes including staff performance management as well as employee development. Within recruitment and selection, it would add to literature to understand the perspective of the candidates within the South African context. The ethical considerations of AI adoption in recruitment and selection and particularly on its use in candidate engagement should requires future exploration. Overall, these future research directions could help to build upon the current findings and provide a more comprehensive understanding of the potential benefits and challenges of adopting AI in recruitment and selection.

5.5. Conclusion

This chapter has provided an overview of the findings from the study on AI adoption in recruitment and selection among South African universities. Research questions were addressed through the analysis of both descriptive statistics and PLS-SEM. The findings

revealed that South African universities are not hesitant in adopting AI in their recruitment processes and that cost effectiveness, relative advantages of AI over traditional methods, senior management backing, pressure from competitive adopting institutions, AI vendors support, and government adoption funding sponsorship supportively encourage AI adoption. However, privacy and security matters were identified as a barrier to AI adoption in recruitment and selection.

The implications of these findings are significant for both practitioners and policymakers. The potential benefits of AI adoption in recruitment and selection include increased efficiency, improved decision-making, and reduced bias. However, challenges such as security and privacy concerns and the need for ongoing training and support should be considered. To enhance AI adoption in recruitment and selection, universities should prioritise building awareness and knowledge among top management, securing adequate financial resources, and creating a supportive organizational culture that encourages experimentation and learning. Policymakers should consider developing guidelines and standards for the ethical utilisation of AI in talent acquisition. The research contributes to existing literature through provision of empirical evidence on factors influencing the embedding of artificial intelligence in recruitment and selection processes of South African universities. The study also highlights the need for further research in this area to address the identified limitations and to explore the potential benefits and challenges of artificial intelligence adoption in recruitment and selection in different contexts.

In conclusion, the study's findings suggest that the adoption of AI in recruitment and selection in South African universities has significant potential benefits, but also some challenges that need to be addressed. Universities and policymakers should work together to promote the ethical use of AI, while also addressing the identified challenges. Additional studies are required to explore the potential likely advantages and disadvantages of AI adoption in different contexts and to develop strategies to enhance AI adoption in recruitment and selection.

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Appendix 1.1: Data Collection Instrument

Data Collection Instrument: Survey Questionnaire:

The adoption of Artificial Intelligence within traditional recruitment and selection process of South African universities.

Informed Consent:

Dear Research Participant,

You are invited to complete a research questionnaire for my MBA study. The purpose of the study is to understand the level of adoption of artificial intelligence within traditional recruitment and selection processes of South African universities. Understanding factors that influence such adoption will enable recommendations for strategic human resource recruitment and selection technological framework to enhance talent management decisions. The study will also add value to the universities in assisting managers to strategically manage adoption of intelligent systems in recruitment and selection.

Using the Technology Organisation and Environment (TOE) framework, the research questionnaire comprises of three sections, namely section A, B & C. Section A pertain factors from a Technology context subconstructs that influence adoption of artificial intelligence. Section B comprises of questions on Organisation context subconstructs while Section C comprises of questions on Environmental context subconstructs factors that affect adoption of artificial intelligence.

Kindly follow the instructions and answer ALL questions from ALL the sections. There is no right or wrong answer to any of these questions; answers are intended to determine your view point based on your observation and experience. Completing the questionnaire will take more or less 10 minutes of your time. Your answers will be treated in strict confidence. You need not reveal your identity, and participation is voluntary. The information supplied will be used solely for research purposes and in accordance with the ethical rules of research applicable at Wits Business School.

By completing the questionnaire, you have read the informed consent and agree to participate in this research. Any queries can be addressed to Mr Godwin Murerwa at 078 111 9007, Email address godwin@skillplace.co.za. Your cooperation and participation in the study will be greatly appreciated.

Instructions for completing the questionnaire:

Please indicate the extent to which you agree or disagree with the questions below, using the following scale:

Strongly Disagree	Disagree	Neither agree nor disagree	Agree	Strongly Agree
1	2	3	4	5

	Strongly Disagree	Disagree	Neither agree nor disagree	Agree	Strongly Agree
Section A: Technology Context *Cost-effectiveness (COS):*					
1. Adoption of Artificial Intelligence for recruitment and selection is cost-effective than the traditional recruitment and selection technologies.	1	2	3	4	5
2. Adoption of Artificial Intelligence for recruitment and selection saves the cost of other technology and manpower required for recruitment and selection.	1	2	3	4	5
3. Adoption of Artificial Intelligence in recruitment and selection saves time and effort related to costs required for recruitment and selection.	1	2	3	4	5
Technology Context *Relative advantage (REA):*					
4. Adoption of Artificial Intelligence helps Human Resources Practitioners to select the right candidates.	1	2	3	4	5
5. Adoption of Artificial Intelligence helps in a better quality of decisions for recruiting and selecting candidates.	1	2	3	4	5
6. Adoption of Artificial Intelligence improves the effectiveness of recruitment and selection decisions and actions.	1	2	3	4	5
7. Adoption of Artificial Intelligence speeds up the recruitment and selection decisions.	1	2	3	4	5

8. Adoption of Artificial Intelligence provides better control over the recruitment and selection function.	1	2	3	4	5
Technology Context *Security & privacy concerns (SNP):*					
9. We feel that recruitment and selection data transmitted in Artificial Intelligence is not secure.	1	2	3	4	5
10. We feel that recruitment and selection data stored and used by Artificial Intelligence lacks in confidentiality and privacy.	1	2	3	4	5
11. We believe that Artificial Intelligence is not safe as there is possibility of error due to the algorithms in Artificial Intelligence.	1	2	3	4	5
Section B: Organization Context *HR readiness (HRR):*					
12. Human Resources department has financial budget to adopt Artificial Intelligence for recruitment and selection.	1	2	3	4	5
13. Human Resources department personnel are expert to use Artificial Intelligence for recruitment and selection.	1	2	3	4	5
14. Human Resources leaders in universities are willing to invest in Artificial Intelligence for recruitment and selection.	1	2	3	4	5
Organization Context *Top management Support (TMS):*					
15. Top management provide support for the adoption of Artificial Intelligence for recruitment and selection.	1	2	3	4	5
16. Top management offer funds for adoption of Artificial Intelligence for recruitment and selection.	1	2	3	4	5
17. Top management knows the benefits of adoption of Artificial Intelligence for recruitment and selection.	1	2	3	4	5
Section C: Environmental Context *Competitive pressure (COM):*					
18. Our university has pressure of adoption of Artificial Intelligence for	1	2	3	4	5

recruitment and selection due to competitors' adoption of Artificial Intelligence for recruitment and selection.					
19. Recruitment and Selection practice across universities forced us to adopt Artificial Intelligence for recruitment and selection.	1	2	3	4	5
20. Our university keeps a watch on competitors for the Artificial Intelligence technology used for recruitment and selection.	1	2	3	4	5
Environmental Context *Support from technology vendors (STV):*					
21. Artificial Intelligence training is fairly provided by the vendors of Artificial Intelligence for recruitment and selection.	1	2	3	4	5
22. Artificial Intelligence vendors provide adequate technical support during implementation of Artificial Intelligence for recruitment and selection.	1	2	3	4	5
23. Artificial Intelligence vendors provide adequate technical support after implementation of Artificial Intelligence for recruitment and selection.	1	2	3	4	5
Environmental Context *Support from Government (SFG):*					
24. The Government understands the need for adoption of Artificial Intelligence for recruitment and selection in universities.	1	2	3	4	5
25. The Government through the Department of Higher Education and Technology and other entities supports the implementation of Artificial Intelligence for Recruitment and Selection.	1	2	3	4	5
26. The Government offer funds for the adoption of Artificial Intelligence for recruitment and selection in universities.	1	2	3	4	5

Appendix 2.1: Ethical Clearance: Wits Business School

Graduate School of Business Administration
University of the Witwatersrand, Johannesburg

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

Ethics Clearance Certificate

Ethics protocol number: WBS/BA2504617/141
This certificate is only valid with a legitimate ethics protocol number and signed by the Researcher (below).

This certificate is only valid if accompanied by formal permission from the relevant stakeholder(s).

Project title	The adoption of Artificial Intelligence within traditional recruitment and selection process of South African universities
Investigator / Researcher	Mr Godwin Murerwa
Nature of Project	MBA (Research Article)
Decision of the Committee	Approved, provided stakeholders and participants are guaranteed anonymity and confidentiality.
Issue Date of Certificate	2022-09-01
Expiry date	Date of submission of the project / research report
Chairperson	Prof Anthony Stacey ☎ +27 11 717 3587 +27 82 880 4531 anthony.stacey@wits.ac.za

Declaration by Researcher

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

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

Signature

01 September 2022
Date:

Appendix 2.2: Gatekeepers Permission: Rhodes University

RHODES UNIVERSITY
Where leaders learn

Rhodes University Human Research Ethics Committee
PO Box 94, Makhanda, 6149 South Africa
Email: ethics-committee@ru.ac.za

www.ru.ac.za/research/research/ethics
NHREC Registration No. REC-241114-045

02 November 2022

Mr Godwin Murerwa
Graduate School of Business Administration
University of Witwatersrand

Dear Mr Murerwa

GATEKEEPERS PERMISSION TO CONDUCT RESEARCH WITH RHODES UNIVERSITY STUDENTS

Name of research proposal: The adoption of Artificial Intelligence within traditional recruitment and selection process of South African universities.

This serves to confirm that you have been granted permission to conduct your proposed research at Rhodes University.

Kindly be advised that the University is not obliged to make any arrangements in terms of this research, and that the onus is on the researcher.

This letter is valid from 02 November 2022 to 02 November 2023.

Sincerely,

Janet Hayward

Dr Janet Hayward
Chair: Rhodes University Human Research Ethics Committee

AUTHORITY TO GRANT GATEKEEPER'S PERMISSION TO CONDUCT LOW AND MEDIUM-RISK RESEARCH IN RELATION TO STUDENTS AT RHODES UNIVERSITY HAS BEEN DELEGATED TO THE RELEVANT RESEARCH ETHICS COMMITTEE CHAIRS AS APPROVED BY RHODES UNIVERSITY SENATE ON 19 AUGUST 2022

Appendix 2.3: Gatekeepers Permission: University of Free State

UNIVERSITY OF THE FREE STATE
UNIVERSITEIT VAN DIE VRYSTAAT
YUNIVESITHI YA FREISTATA

UFS
UV

Office of the Vice-Rector: Research and Internationalisation
Kantoor van die Viserektor: Navorsing en Internasionalisering

14-Oct-2022

Dear Mr Godwin Murerwa

UFS AUTHORITIES APPROVAL

Research Project Title:
The adoption of Artificial Intelligence within traditional recruitment and selection process of South African universities

This letter serves as confirmation that you have received reciprocal ethical approval, with the reference number UFS-HSD2022/1778 from the University of the Free State (UFS). It also confirms approval to collect data from the UFS students and/or staff members.

Kind Regards

PROF RC WITTHUHN
VICE-RECTOR: RESEARCH & INTERNATIONALISATION
CHAIR: SENATE RESEARCH ETHICS COMMITTEE

205 Nelson Mandela Drive/Rylaan
Park West/Parkwes
Bloemfontein 9301
South Africa/Suid-Afrika

P.O. Box / Posbus 339
Bloemfontein 9300
South Africa / Suid-Afrika
T: +27(0)51 401 2116
F: +27(0)51 401 3762
WitthuhnRC@ufs.ac.za
www.ufs.ac.za

Appendix 2.4: Gatekeepers Permission: Nelson Mandela University

NELSON MANDELA
UNIVERSITY

PO Box 77000, Nelson Mandela University, Port Elizabeth, 6031, South Africa mandela.ac.za

Chairperson: Research Ethics Committee (Human)
Tel: +27 (0)41 504 3624
Dalray.Gradidge@mandela.ac.za

NHREC registration nr: REC-042508-025

Ref: [H22-BES-BUS-EAP-001] / Approval: 20 February 2023 – 20 February 2024

20 February 2023

Dear Dr Venter

THE ADOPTION OF ARTIFICIAL INTELLIGENCE WITHIN RECRUITMENT AND SELECTION PROCESSES OF SOUTH AFRICAN UNIVERSITIES

PRP: Dr R Venter
PI: Mr G Murerwa

Your application for ethics approval to conduct research at Nelson Mandela University has been considered by the REC-H on the basis that the study has been duly vetted and approved by the Wits Business School, Research Ethics Committee.

Kindly use the following ethics reference number **H22-BES-BUS-EAP-001** together with your University's ethics clearance number in any correspondence with gatekeepers and participants at the University. Ethics clearance is valid for one year.

Please inform the REC-H, of any changes that may arise during the execution of the study, particularly to the methodology.

It must be noted that the Nelson Mandela University assumes that the Research Ethics Committee responsible for providing the original ethics approval/clearance has undertaken both ethics and scientific review of the protocol according to the National Health Research Ethics Committee (2015) Guidelines, and assumes primary responsibility for oversight with regard to any ethical issues that may arise in the course of the study. The Nelson Mandela University would also wish to be provided with an executive summary of the findings from the research.

We wish you well with the project.

Yours sincerely

Dr D Gradidge
Chairperson: Research Ethics Committee (Human)

cc: Department of Research Development

Appendix 2.5: Gatekeepers Permission: University of KwaZulu-Natal

UNIVERSITY OF KWAZULU-NATAL
INYUVESI YAKWAZULU-NATALI

10 October 2022

Mr Godwin Murerwa
Graduate School of Business Administration
University of the Witwatersrand
Email: godwin@skillsplace.co.za Robert.Venter@wits.ac.za

Dear Mr Murerwa

RE: PERMISSION TO CONDUCT RESEARCH

Gatekeeper's permission is hereby granted for you to conduct research at the University of KwaZulu-Natal (UKZN), towards your postgraduate degree, provided Ethical clearance has been obtained. We note the title of your research project is:

"The adoption of Artificial Intelligence within traditional recruitment and selection process of South African universities."

It is noted that you will be constituting your sample as follows:

- With a request for responses on the website. The questionnaire must be placed on the notice system http://notices.ukzn.ac.za. A copy of this letter (Gatekeeper's approval) must be simultaneously sent to (govenderlog@ukzn.ac.za) or (ramkissoonb@ukzn.ac.za).

Please ensure that the following appears on your notice/questionnaire:

- Ethical clearance number;
- Research title and details of the research, the researcher and the supervisor;
- Consent form is attached to the notice/questionnaire and to be signed by user before he/she fills in questionnaire;
- gatekeepers approval by the Registrar.

You are not authorized to contact staff and students using the 'Microsoft Outlook' address book. Identity numbers and email addresses of individuals are not a matter of public record and are protected according to Section 14 of the South African Constitution, as well as the Protection of Public Information Act. For the release of such information over to yourself for research purposes, the University of KwaZulu-Natal will need express consent from the relevant data subjects. Data collected must be treated with due confidentiality and anonymity.

Yours sincerely

Dr KE CLELAND: REGISTRAR

Appendix 2.6: Gatekeepers Permission: University of Venda

Research and Innovation
Office of the Director

Date: 19th September 2022

Mr Godwin Murerwa
Wits Business School

Email: godwin@skillplace.co.za

Dear **Mr. G Murerwa**

Permission to conduct Research at the University of Venda

You are hereby granted permission to conduct research at the University of Venda.

The research will be based on your Masters research title: ***"The adoption of Artificial Intelligence within traditional recruitment and selection processes of South African universities".*** registered at the **Wits Business School**.

Supervisor: Dr Robert Venter

Approval period: September 2022 – September 2023

The conditions are that all the data pertaining to University of Venda will be treated in accordance with the Ethical Principles and that will be shared with the University upon completion of the project. In addition, consent should be sought by you as a researcher from participants.

Attached is our policy on ethics.

Thank you

.....
Prof VO Netshandama

Chairperson: UREC

UNIVERSITY OF VENDA
OFFICE OF THE DIRECTOR
RESEARCH AND INNOVATION
2022 -09- 27
Private Bag X5050
Thohoyandou 0950

Cc: Prof N Feza (DVC Research and Postgraduate Studies)

Cc: Senior Prof GE Ekosse (Director Research and Innovation)

Cc: Prof MS Mashau (Chairperson RESSC)

University of Venda

UNIVERSITY OF VENDA
PRIVATE BAG X5050, THOHOYANDOU, 0950. LIMPOPO PROVINCE. SOUTH AFRICA
TELEPHONE 015 962 8313 / 8504. FAX 015 962 9060
Email: research@univen.ac.za

"A quality driven, financially sustainable, rural-based comprehensive University"

Appendix 2.7: Gatekeepers Permission: University of Limpopo

University of Limpopo
Office of the Registrar
Private Bag X1106, Sovenga, 0727, South Africa
Tel: (015) 268 2407, Fax: (015) 268 3048, Email: Kwena.Masha@ul.ac.za/Retha.Balie@ul.ac.za

09 November 2022

G Murerwa

Email: Godwin@skillplace.co.za

Dear G Murerwa,

GATEKEEPER PERMISSION TO CONDUCT RESEARCH

TITLE: **EXPLORATION OF THE ADOPTION OF ARTIFICIAL INTELLIGENCE IN THE TRADITIONAL RECRUITMENT AND SELECTION PROCESS OF SOUTH AFRICAN UNIVERSITIES**

RESEARCHER/S: **G Murerwa**
SUPERVISOR: **Dr. R Venter**
CO-SUPERVISOR/S: **N/A**
INSTITUTION: **University of Witwatersrand (Wits Business School)**

Kindly be informed that Gatekeeper permission is granted to you to conduct research at the University of Limpopo entitled: "**Exploration of the adoption of Artificial Intelligence in the traditional recruitment and selection process of South African Unviersities**"

Regards,

PROF. JK MASHA
UNIVERSITY REGISTRAR

Cc. Prof. RJ Singh: Deputy Vice-Chancellor; Research, Innovation and Partnerships
Prof. RN Madadzhe: Deputy Vice-Chancellor: Teaching and Learning
Dr. T Mabila, Director: Research Development and Administration
Prof. D Maposa – Chairperson: Research and Ethics Committee
Ms M Hutamo – Assistant: Ethics Secretarist
Ms A Ngobe – TREC Secretariat

Finding solutions for Africa

Appendix 2.8: Gatekeepers Permission: Durban University of Technology

Directorate for Research and Postgraduate Support
Durban University of Technology
Open House
P.O. Box 1334, Durban 4000
Tel.: 031-3732576/7
Fax: 031-3732946

10 October 2022

Mr Godwin Murerwa
c/o Wits Business School
University of the Witwatersrand

Dear Mr Murerwa

PERMISSION TO CONDUCT RESEARCH AT THE DUT

Your email correspondence in respect of the above refers. I am pleased to inform you that the Institutional Research and Innovation Committee (IRIC) has granted **Gatekeeper Permission** for you to conduct your research "The adoption of Artificial Intelligence within traditional recruitment and selection process of South African universities" at the Durban University of Technology.

The DUT may impose any other condition it deems appropriate in the circumstances having regard to nature and extent of access to and use of information requested.

We would be grateful if a summary of your key research findings would be submitted to the IRIC on completion of your studies.

Kind regards.
Yours sincerely

MS V GOVENDER
ACTING-DIRECTOR: RESEARCH AND POSTGRADUATE SUPPORT DIRECTORATE

Appendix 2.9: Gatekeepers Permission: University of Johannesburg

27 September 2022

Godwin Murerwa
University of the Witwatersrand (WITS)

Dear Godwin Murerwa

PERMISSION TO CONDUCT RESEARCH AT THE UNIVERSITY OF JOHANNESBURG

The request for the project titled *The adoption of Artificial Intelligence within traditional recruitment and selection process of South African universities* refers. Permission is granted to conduct this study at the University of Johannesburg (UJ).

Please note that the granting of permission does not make it mandatory for UJ students and/or staff to participate in the study. As the reseacher/applicant, you will need to engage with potential participants to obtain their consent to participate in the study.

Should you require assistance in distributing the survey to UJ students and/or staff, kindly send a brief description of your study together with the link to where participants can access the survery to tdewet@uj.ac.za, copying hemalij@uj.ac.za and rloots@uj.ac.za.

Sincerely

Dr Ndivhuwo Luruli
Executive Director: Research and Innovation
Email: nmluruli@uj.ac.za

Cnr Kingsway and University Road Auckland Park • PO Box 524 Auckland Park 2006 • +27 11 559 2911 • uj.ac.za
Auckland Park Bunting Campus • Auckland Park Campus • Doornfontein Campus • Soweto Campus